Aggregate Megatrends and the Risk of Labour Market Exclusion Across Europe

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Abstract

Labour market exclusion represents a major concern in several European economies, particularly affecting highly exposed demographic groups. We investigate whether four main megatrends – namely, digitalisation, globalisation, climate change, and demographic change – have exacerbated the risk of exclusion between 2009 and 2019. First, we use Labour Force Survey (LFS) data for the European Union (EU) 27 countries and the United Kingdom to identify countries and demographic groups most exposed to long-term unemployment and inactivity, and we collect detailed information on the evolution of the four megatrends across Europe from various sources. In the empirical analysis, we compute changes in the probability of individuals to fall into long-term unemployment and inactivity because of exposure to aggregate megatrends, controlling for several individual and country/region-specific characteristics, and potential selection mechanisms. Our results highlight that, on average, digitalisation has the more significant effect on labour market exclusion. Specifically, automation-related innovations significantly increase the probability of long-term unemployment, while the adoption of automation technologies significantly raises the chances of falling into inactivity. Although the overall effect of megatrends is small in magnitude, we uncover that such effects are heterogeneous across demographic groups.

Keywords: Long-term unemployment; digitalisation; globalisation; climate change; demographic change.

JEL codes: J11; J64; F16; O33; Q54.

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1. Introduction

Labour market exclusion has attracted significant academic interest over the past decades given the profound implications for workers facing long-term unemployment, skill mismatch and the consequent risk of falling into inactivity (Gutiérrez and Guillén, 2000; Koen et al., 2013; Fang and Gunderson, 2015; Apergis and Apergis, 2020; Miyamoto and Suphaphiphat, 2020). First, from an economic viewpoint, excluded individuals face higher barriers to employability leading to a raised risk of poverty (Koen et al., 2013; Krueger et al., 2014; Ruesga-Benito et al., 2018). More generally, from a social and psychological perspective, prolonged unemployment and involuntary inactivity are associated with self-worth issues, vulnerability, poor motivation, or scarce social links (Fang and Gunderson, 2015).

Nowadays, the problem of individuals falling into exclusion conditions represents a concern in several European countries, especially those where general unemployment levels are already high, such as Italy and Spain, among the others (Gutiérrez and Guillén, 2000). As a result, growing governments' consideration has proceeded hand in hand with academic analysis of the effectiveness of policy actions undertaken to mitigate such conditions. For instance, considerable attention has been paid to the potential worsening of these phenomena in times of economic crisis (Caroleo et al., 2020), rising inequality (Fortin et al., 2012; Miyamoto and Suphaphiphat, 2020), and to the subsequent recovery – lately, from the Covid-19 pandemic (European Commission, 2021). These studies highlight that long-term unemployment and inactivity outcomes tend to be more procyclical and exacerbated by general economic conditions, growing skill mismatch and labour market inefficiencies. Furthermore, vulnerable workers may lack the skills and education to suit effectively in the new digital, green, and ever global economy. Indeed, returns to education remain high and the shortcomings associated with dropping out of school are substantial (Gunderson and Oreopoulos, 2010). Additionally, workers at risk of exclusion may be permanently and involuntarily trapped in low-quality jobs, often involving non-standard employment, preventing them from finding higher-quality jobs (Fang and Gunderson, 2015).

However, extant research has dedicated limited attention to the role of evolving macroeconomic, structural, and social trends that have emerged in recent years, which may influence the individual propensity to fall in exclusion conditions. We address this gap by analysing how current megatrends affect such propensity, on top of traditional aggregate and individual factors.

Specifically, the recent decades have witnessed numerous structural and compositional transformations in the working population, hitting across different demographic groups, i.e. from younger to elder workers, across gender, and between workers possessing different educational attainment. These conditions have been exacerbated by labour market changes related with various megatrends, which have become ever more relevant over the past decade. First, latest forms of technological change and digitalisation – automation forms like artificial intelligence (AI) and advanced manufacturing technologies of the Industry 4.0 (I4.0) – have fostered a renewed interest in the effect of technological transformations on the labour market (e.g., Acemoglu and Restrepo, 2020). Second, trends in globalisation, with the emergence of Global Value Chains (GVCs) in early '90s – and the resulting international division of labour across value chain activities – have profoundly changed the structure and concentration of trade, related productive tasks, hence labour demand (e.g., Grossman and Rossi-Hansberg, 2008). Third, the challenges introduced by climate change and the recent commitment to shift towards a green economy, together with the revived ambition to reduce greenhouse gas emissions – for instance, signalled by the European Green Deal and the Inflation Reduction Act – are pushing through further structural changes across economies, ranging from subsidies to the development of green technologies to investments in the production of clean energy, which can have significant effect on the labour market (e.g., Markandya et al., 2016). Fourth, changes in the long-run demographic trends (e.g., aging and immigration) may play a role in directing employment dynamics by directly affecting labour supply (e.g., Abraham and Kearney, 2020). All these changes are creating winner and losers, setting the condition for a rising number of workers to face the risk of labour market exclusion; thus, further contributing to increasing inequality.

The paper contributes to this literature by providing a comprehensive analysis of the European labour market between the aftermath of the 2008's global financial crisis and before the 2020's Covid-19 global pandemic, i.e. over the 2009-2019 period. Specifically, we use large-scale microdata from the Labour Force Survey (LFS) for 27 European Union (EU) countries and the United Kingdom to understand and track the persistency or the evolution of long-term unemployment and inactivity across active population. At the same time, while prior studies only offer a partial picture of these macroeconomic and social changes by focusing only on one, or few, aspects at once, we provide a comprehensive picture of the evolution of the four aggregate megatrends – namely, digitalisation, globalisation, climate, and demographic changes – across European countries and over time. Specifically, we distinguish different aspects related with each megatrend: for instance, we investigate the digitalisation process by specifically measuring the adoption of more advanced forms of physical capital (i.e., industrial robots, additive manufacturing, and internet-of-things) and the innovation process behind information and communication technologies (ICTs), automation technologies, and other advanced technologies (e.g., nanotechnologies). Similarly, globalisation is measured using a set of indicators capturing GVC participation, trade openness and foreign direct investments (FDIs). We explore climate changes by looking at a broad range of metrics, like more traditional measures such as CO_2 emissions, and analysing data on extreme climate events like droughts, extreme precipitations, heat, and cold waves. Finally, we investigate several aspects of demographic change, such as population aging, fertility rates and migration. The second main contribution of our work relates to the econometric analysis, which explores the direct effect of these megatrends on changes in the probability of individuals to fall in exclusion outcomes. We control for a large set of individual and country/region-specific characteristics, further accounting for the selection mechanisms behind categorisation of individuals who are already unemployed (or inactive) as excluded categories.

Our results highlight that, on average, the overall effect of megatrends is very limited in magnitude, although digitalisation (both looking at the adoption and the innovation side) significantly increases the probability of long-term unemployment and inactivity. Nonetheless, even when the estimated average marginal effects of megatrends are not significant, we uncover some heterogeneity of the estimated relationships with the probability of exclusion when accounting for the moderating role of demographic characteristics (i.e., gender, age group and educational attainment). Our analysis underscores that the probability of long-term unemployment is significantly associated with a number of individual demographic characteristics and with the diffusion of advanced technologies at the country level. While the latter are found to play a role, although rather minor, other megatrends result to be largely irrelevant.

The rest of the paper is structured as follows. The next section provides an overview of the main mechanisms through which each megatrend may affect labour market outcomes and, in turn, the probability of labour market exclusion. In Section 3, we discuss data sources and outline our econometric strategy. Section 4 delves into the stylised facts on long-term unemployment across Europe, as well as into the evolution of megatrends. Section 5 presents the econometric results, while Section 6 discusses findings and concludes.

2. Theoretical background

In this section, we discuss the underlying mechanisms behind the effect that each megatrend can exert on labour demand and supply, thus leading to labour market exclusion and long-term unemployment, with a focus on how age, education and gender can moderate these relations.

2.1. Digitalisation

A wide literature on the relationship between the latest wave of technological change (i.e., digital and automation technologies) and employment has proliferated over the past decade. From a theoretical perspective, the relationship between technology and employment has long been studied under the lens of the so-called *compensation theory* (Freeman et al., 1982; Vivarelli, 1995; see Vivarelli, 2014; Montobbio et al., 2023 for comprehensive reviews), highlighting different – direct and indirect – compensation mechanisms of a classical, neoclassical, or Keynesian nature. Notably, this stream of the technology-employment literature has focussed on modelling the distinct effects of *product* and *process* innovations (e.g., more advanced and productive vintages of machines) for countries, sectors and firms (e.g., Bogliacino and Pianta, 2010; Bianchini and Pellegrino, 2019).

Lately, with the advent of automation technologies (e.g., AI, internet-of-things, and industrial robots) the focus has shifted towards modelling the substitution mechanism triggered by new forms of hardware and software, which are able to carry out tasks previously performed by humans. Starting from the '90s, theories of *skill-biased technological change* (SBTC), *routine-biased technological change* (RBTC) and, lately, *task-biased technological change* (TBTC) have emerged (e.g., Autor et al., 2003; Acemoglu and Autor, 2011; Autor, 2013). As highlighted by Acemoglu and Restrepo (2019), highly productive automation technologies generate a *productivity* effect, resulting in an increase in value-added, which may raise labour demand in non-automated tasks. However, with capital deepening (i.e., growing capital-to-labour ratio), automation technologies may take over tasks previously performed by human labour, resulting in a *displacement* effect. Such negative effect may be mitigated, or even counterbalanced, if automation technologies spur new complementary tasks in which humans have a comparative advantage, producing a *reinstatement* effect.

The empirical literature has long investigated the technology-employment nexus (see, for instance, Mondolo, 2022; Filippi et al., 2023; Montobbio et al., 2023 for recent reviews), looking at different levels of aggregation (i.e., individuals, firms, industries, and countries) using different sources of information to proxy technological progress (i.e., survey data, research and development (R&D) or investment expenditures, patent and/or import data). Overall, the empirical evidence is inconclusive when looking at the effects of different technologies on total employment, while results are quite robust in showing labour market polarisation effects, a significant reallocation of jobs across industries, and a consistent change in the task content of different occupations (e.g., Frey and Osborne, 2017; Graetz and Michaels, 2018; Gregory et al., 2019; Acemoglu and Restrepo, 2020; Acemoglu et al., 2020; Bonfiglioli et al., 2020; Camiña et al., 2020; Dauth et al., 2021; Domini et al., 2021, 2022; Felice et al., 2022; Bessen et al., 2023; Mann and Püttmann, 2023).

Extant evidence suggests that digital and automation technologies may be detrimental in the long run for more exposed workers (i.e., performing standardised tasks). To this end, beyond the reinstatement mechanism highlighted above, training and up-skilling programs (i.e., human capital accumulation processes) play a crucial role in reducing the odds of workers being displaced and remain unemployed. Several works have analysed the consequences of automation and digital technologies on unemployed workers' and the effect on the probability of finding new jobs (Olsson and Tåg, 2017; Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Schmidpeter and Winter-Ebmer, 2021). These studies generally highlight that polarisation mechanisms still exist even across unemployed workers, that the lack of digital skills strongly reduce future chances of being re-employed, and that technical training counteracts such additional negative effect of automation.

These mechanisms are likely to self-reinforce the longer workers remain unemployed – with the related risk of becoming inactive –, due to the continuous loss of competences and the rising skill gap. Therefore, we argue that *digital/automation technologies, on average, increase the likelihood of labour market exclusion. Such relationship is likely to be exacerbated by a lower endowment of skills and competences and for older workers that may be at a disadvantage at catching-up in the use of these technologies.*

2.2. Globalisation

The last few decades, starting from the early '90s (Baldwin and López González, 2015), have been characterised by the growing importance of supply-chain trade of intermediates between high-wage (high-tech, frontier) and low-wage (low-tech, laggard) countries, resulting in the formation of highly fragmented international production networks, also called global value chains (e.g., Krugman, 1995; Timmer et al., 2014). GVCs typically involve different types of supply-chain trade – mostly, but not only, *importing-to-produce*, *importing-to-export* and *value-added trade* (Baldwin and López González, 2015) – and imply a profound reorganisation in the international division of labour, with some countries specialising in orchestration activities and others as factory economies (López González et al., 2019; Timmer et al., 2019; Bontadini et al., 2024).

The theoretical literature on GVCs and trade specialisation not only argues that countries tend to specialise in different products (i.e., final goods or intermediates) or activities (i.e., the international fragmentation of functions, such as R&D, marketing, manufacturing, etc.), but also in different tasks (Grossman and Rossi-Hansberg, 2008, 2012), resulting in the ever-growing *functional specialisation* of trade (Timmer et al., 2019). With that, the relative composition of employment and the demand for labour in both advanced and developing countries has faced marked transformations. For instance, growing globalisation and functional specialisation in advanced economies is likely to trigger an up-skilling of the labour force, together with a shift away from (towards) low (high) value-adding tasks (Grossman and Rossi-Hansberg, 2008, 2012). Conversely, developing economies mostly conducting manufacturing operations are likely to retain low value-adding tasks. This traditionally creates large opportunities for unskilled workers, mostly concentrated around the activity of multinational's subsidiaries (Ibarra-Olivo and Rodríguez-Pose, 2022), while also reducing returns to education and limiting the potential for workforce's up-skilling (Ibarra-Olivo, 2021).

Empirical evidence suggests that more advanced countries tend to configure as headquarter economies in the global divisions of labour spurred by the emergence of GVCs (Baldwin and López González, 2015). These countries do not experience a reduction in overall employment levels and become more high-skill oriented (Crinò, 2012). Conversely, findings on developing economies are more mixed regarding the overall employment effect, although converging on the rising specialisation in low value-adding activities and tasks (Ma et al., 2019; Banga, 2016), as well as lower returns from education (Ibarra-Olivo, 2021; Ibarra-Olivo and Rodríguez-Pose, 2022). For instance, starting from the 2008's global financial crisis, Europe has experienced a strong polarisation of both employment and industrial specialisation, resulting in the specialisation of (advanced) western countries – Germany, above all – as headquarter economies and GVC orchestrator, contrasted by the stagnating southern periphery (Cirillo and Guarascio, 2015) and the rapidly growing east European economies, who have become the factory of a more regional production network (Pavlínek, 2018).

Therefore, globalisation may imply opposing effects on employment depending on a country positioning along, and its participation to GVCs. On the one hand, globalisation has given way to a major global reallocation of jobs, creating both opportunities and lock-in conditions (Ma et al., 2019; Ibarra-Olivo, 2021). On the other hand, integration in GVCs can raise employment opportunities through demand, productivity, and scale effects (Taglioni and Winkler, 2016; Ma et al., 2019).

At the individual's level, however, these mechanisms are bounded to the endowment of skills and competencies, making excluded workers variably suitable for taking advantage of GVC-related opportunities. On the one hand, individuals facing inactivity or long-term unemployment generally feature lower employability due to the lack of skills and competencies (Miyamoto and Suphaphiphat, 2020). On the other hand, European countries mostly feature advanced levels of economic development, characterised by advanced technological capabilities and a higher demand for skills driving the catching-up of laggard countries in the region (Lamperti et al., 2023). Therefore, we maintain that *the average effect of globalisation on the probability of falling into labour market exclusion conditions is expected to be positive*.

2.3. Climate change

Ever since the first industrial revolution, exponential economic growth and rising living standards have proceeded hand in hand with consumption of natural resources – above all, fossil fuels – (Dell et al., 2014;

Rezai et al., 2018). Nowadays, a common agreement across the scientific community considers such process one of the main determinants of the rapid worldwide increase in temperature and frequency of extreme climate events, resulting in natural disasters (Carleton and Hsiang, 2016; Kahn et al., 2019; Huang et al., 2020).

The literature on the economic implications of climate change has grown over the past decades (see Dell et al., 2014, for a comprehensive review), devoting much attention to the understanding of both long-run and short-run effects on employment (e.g., Rezai et al., 2018; Kahn et al., 2019; Huang et al., 2020; Dasgupta et al., 2021), income distribution (e.g., Rezai et al., 2018; Tol, 2018), as well as changes in jobs and the workplace (e.g., Goods, 2017; Apostel and Barslund, 2024). Both theoretical modelling and empirical analysis of the economic impact of climate change predicts consistent long-run negative effects on economic growth, employment, and income distribution in the case of a *laissez-faire* approach from policymakers and international institutions, while negative effects are largely contained in the presence of proactive mitigation policies (Rezai et al., 2018; Kahn et al., 2019; Dasgupta et al., 2021). Conversely, in the short-run, opposing and heterogeneous effects are likely to arise (Cashin et al., 2017). On the one hand, larger economic growth brought by a low climate change mitigation approach may lead to higher employment from demand growth (Tol, 2018). On the other hand, worsening environmental conditions and more frequent adverse events may trigger labour reallocation mechanisms, migrations, and demand deficit, thus reducing employment and increasing income inequality (Hsiang, 2016; Rezai et al., 2018; Huang et al., 2020).

The large effort required to reduce the environmental impact of economic activities has recently gathered attention, especially in the aftermath of the Covid-19 pandemic, with the newly launched European Green Deal (European Commission, 2023). Consequently, a growing interest has emerged in *green technologies* (Bianchini et al., 2022; often being highly related to digital ones) for climate change mitigation and control, and in new *green jobs* (Bowen et al., 2018; Apostel and Barslund, 2024). The latter are identified based on the environmental friendliness of the tasks and/or skills they require, following similar approaches in the automation literature (e.g., Frey and Osborne, 2017). Indeed, green jobs are estimated to account for a substantial share of total employment in advanced economies (Bowen et al., 2018) and – similarly to jobs facing lower risks of automation – are more skill-intensive and require higher educational attainment (Apostel and Barslund, 2024). For instance, Markandya et al. (2016) estimate the impact on employment of the green transition across Europe to be (on average) positive, leading to a structural shift characterised by a net job-creating trend.

Focusing on short-run effects (like the one analysed in this paper), the negative displacement effects related to natural disasters and extreme events should be outweighed by the positive employment effect spurring from sustained economic growth. Furthermore, another potential compensation mechanism to offset the negative short-run employment effect of climate change may come with the economic boost associated with the green transition, and the related potential for job creation. Nonetheless, the latter positive effect is likely to be limited to highly skilled workers. Therefore, we posit that *the short-run relationship between climate change and labour market exclusion is likely to be negative*.

2.4. Demographic change

The European workforce is undergoing several compositional shifts such as a structural aging trend, a declining working-age population share (Cruz and Ahmed, 2018) and a growing female labour force participation (European Commission, 2021). Key transformations also relate to the asymmetric effect of fertility on labour participation and the employment outcomes of parents (Reher, 2011; Blau and Winkler, 2017), and to gender-related wage inequality in times of crisis (Perugini et al., 2019). Similarly, migration inflows have long been studied, highlighting that fears of job-stealing phenomena towards natives are overstated (Wilson and Jaynes, 2000). On the contrary, migration inflows may affect the distribution of skills within countries, causing the occupational upgrading of natives. Immigrants usually are low-skilled and specialise in manual tasks, while natives specialise in cognitive tasks requiring advanced competencies such as interactive and communication skills (D'Amuri and Peri, 2014). Furthermore, net migration rates positively affect the labour income share (D'Albis et al., 2021).

Economic theory suggests that employment, unemployment, and inactivity dynamics are strongly influenced by and interrelated with both business cycles and changes in demographic composition (Barnichon and Mesters, 2018). The long-run nature of these changes results in marked impacts on economic growth and poverty (Aksoy et al., 2016; Cruz and Ahmed, 2018), but also play a crucial role in influencing other aggregate mechanisms, above all technological change. For instance, Acemoglu and Restrepo (2022) argue that population aging leads to higher automation due to the induced shortage of middle-aged workers. Basso and Jimeno (2020) analyse how decreasing fertility and mortality rates boost automation and – by affecting labour supply, savings and interest rates, and the efficiency of R&D – eventually leads to lower economic growth.

Conversely, short-run economic effects induced by demographic change are likely to be modest, since shifts in the demographic composition of the population takes time to affect other variables like savings, human and physical capital accumulation, which in turn affect economic growth (Cruz and Ahmed, 2018).

Indeed, phenomena like population aging and changes in fertility and mortality rates tends to be slow-moving and persistent over time (Barnichon and Mesters, 2018), making sensible variation observable over longer periods. Furthermore, these variables feature a distinct heterogeneity across countries and regions, not limited to the distinction between developed and developing economies.

Recent evidence suggests that, in advanced economies, demographic changes – mainly, population aging – favour younger and highly-skilled workers, while immigration only play a minor role in affecting employment dynamics (Docquier et al., 2018). Demographic changes may further reduce the chances of employability for those individuals already trapped in a condition of protracted (i.e., long-term) unemployment (Forsythe and Wu, 2021). Therefore, we argue that *the short-run relationship between demographic changes and exclusion outcomes, on average, is likely to be positive. Such relationship is also likely to be less severe for younger and more educated individuals.*

3. Methodology

3.1. Main data sources

The empirical analysis is conducted at the individual level. To this end, as the main data source, 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. LFS' microdata covers both active and inactive population ranging between age 15 and 64, and includes highly detailed information on employment, unemployment and inactivity status – which we use to build our dependent variable, capturing long-term unemployment outcome –, as well as 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 urbanisation and several others.[2] While microdata are anonymised, it is possible in principle to track surveyed people over time by means of a combination of individual, country, and household identifiers. Yet, this is hardly achievable in practice since only few thousands of individuals (over tens of millions) can be tracked longitudinally over our observation period (and, nonetheless, not every year). 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 a number of preliminary cleaning and harmonisation steps aimed at reconciling

[2] 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, several additional variables delving into the duration and the reason for being unemployed or inactive are reported.

variables names, formatting of collected answers, and level of aggregation for the information of interest to our work.[3] We then discarded all individuals for which key information common to employed, unemployed, and inactive individuals was missing.[4] This procedure resulted in a final sample of about 29 million people, 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 with official aggregate LFS statistics. Such very large sample is used only for descriptive purposes, while in the econometric analysis we rely on a representative sample of about 10% the original size, stratified by country, NUTS-2 region, year, employment/activity status, gender, age group, educational attainment, nationality, country of birth, years of residency, and degree of urbanisation of the place where the individual lives.

The key explanatory variables capturing the four megatrends – namely, digitalisation, globalisation, climate, and demographic changes – come from a variety of sources. Data on *digitalisation* refers to adoption of advanced manufacturing technologies (i.e., industrial robots, additive manufacturing, and internet-of-things) as defined by Castellani et al. (2022). Following the authors, technology adoption is proxied by a country's imports of related capital goods at the 8-digit level of product disaggregation and sourced by Eurostat's Comext database.[5] This trade-related approach of measuring technology adoption is increasingly used in many studies (see, among the others, Acemoglu et al., 2020; Bonfiglioli et al., 2020; Domini et al., 2021; Acemoglu and Restrepo, 2022). Data on innovation activity in ICTs, automation technologies such as AI, and other advanced technologies like nanotechnologies comes from OECD REGPAT database. Specifically, we consider each country's number of patent applications filed at the European Patent Office (EPO), using priority date, applying fractional counting to distribute patents across countries, and considering inventor's country of residence.

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[3] 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).

[4] The only exception relates to information on educational attainment. Indeed, 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. We checked for potential representativeness issues resulting from such procedure by looking at official Eurostat data. Furthermore, to account for the potential bias resulting from the imputation, we include a dummy variable identifying imputed observations in each of our econometric specifications.

[5] 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. (2023) for an empirical application. For descriptive purposes, in the Appendix we also report data on exports, production (sourced from Eurostat's Prodcom dataset) and net consumption (i.e., imports – exports + production) of the three advanced manufacturing technologies.

Globalisation data on country-level total participation in GVCs are sourced from OECD's Trade in Value Added (TiVa) database, 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. Additionally, we compute a country's trade openness (i.e., the sum of exports and imports over GDP) and FDI openness (i.e., the sum of inward FDIs and outward FDIs over GDP) using data sourced from the World Bank.

Data on *climate change* comes from OECD database on climate hazards.[6] We use land-related information on extreme climate events such as droughts (as measured by the % change in soil moisture) and heavy precipitations (as measured by the % of land exposed for less than one week, and for between one and two weeks). We also source population-related information on extreme events across European countries, such as exposure to hot days, tropical nights, and icing days (all measured as the % of the total population exposed to such events for up to two weeks). Additionally, we resort to more traditional measures of climate change, such as country-level CO_2 emissions (measured in total number of tonnes produced) and mortality from a range of pollutants including ozone, lead, PM2.5, and radon (measured in number of deaths per million inhabitants). As discussed in Section 2.3, the latter two measures directly relate to the consumption of natural resources.

Finally, we use data on each country's *demographic characteristics* from OECD and Eurostat databases. We measure the shares of total population falling into three categories: below age 15 (i.e., youths), between age 15 and 64 (i.e., working age population), and above age 65 (i.e., elderly population). In addition, we exploit information on fertility rates (measured as the number of children per woman), life expectancy (measured as the number of expected life years at birth), and net migration rates (measured as the difference between inflows of migrants and outflows of expatriates over total population).

We further control for additional country-specific characteristics such as real GDP, the share of R&D expenditure in GDP, the share of agricultural sector value added in GDP, the share of manufacturing sector value added in GDP, and the share of service sector value added in GDP. We source data for these additional controls from the World Bank.

3.2. Variables

The main dependent variable used is a dummy assuming value 1 if the individual experience a condition of long-term unemployment, as defined by a duration longer than one year, and 0 otherwise. Depending

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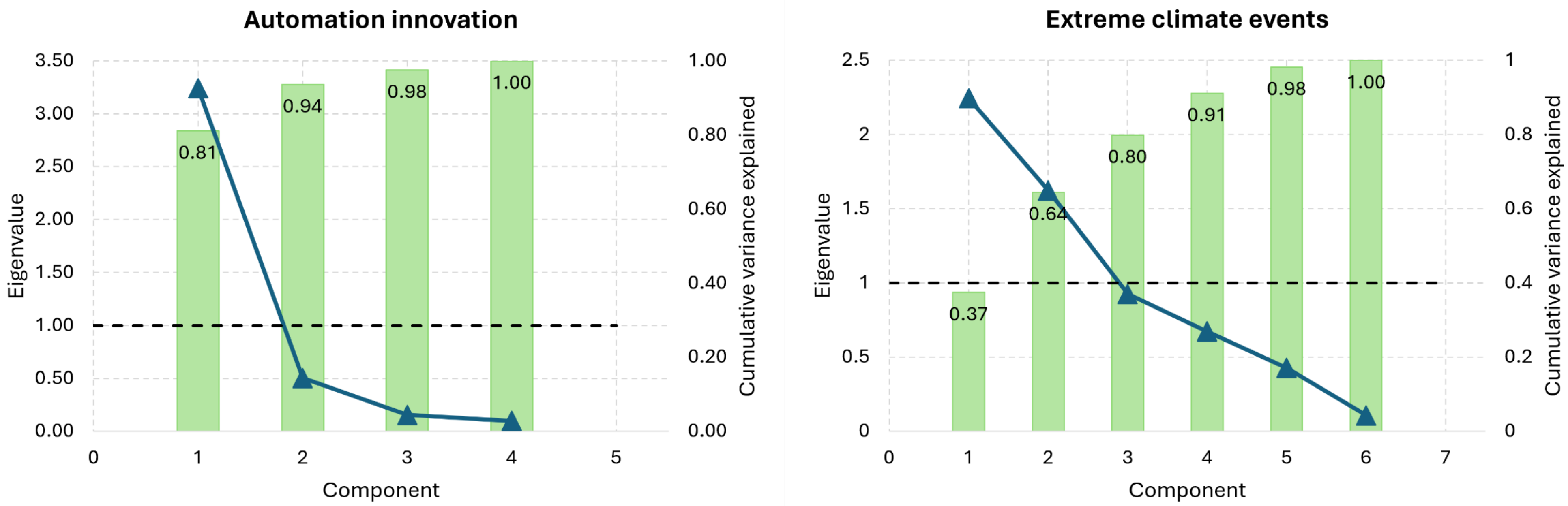
[6] See https://data-explorer.oecd.org.

on the specifications, we also use additional dependent variables, such as a dummy assuming value 1 if the individual is unemployed and 0 otherwise, and a dummy assuming value 1 if the individual is inactive and 0 otherwise, as alternative dependent variables.

As for the main explanatory variables, we preliminary check for the presence of high correlation values and potential multicollinearity issues by means of variance inflation factors (VIFs). This highlights that some of the variables described in the previous section may create multicollinearity issues. Therefore, we exclude pollutants-related mortality (as highly correlated with real GDP and CO_2 emissions), life expectancy (as highly correlated with real GDP), and we keep only the share individuals aged over 65 in total population.[7] In order to further reduce the number of key explanatory variables – and, in turn, the complexity of our econometric model – we performed a principal component analysis (PCA) on innovation and extreme climate events variables. Figure 1 presents the results of the PCAs: patent data on ICTs, AI, additive manufacturing, and nanotechnologies are all well-measured by one principal component (eigenvalue > 1), capturing about 81% of the total variance. Similarly, extreme climate events are sufficiently well-measured by the first two principal components, cumulatively capturing about 65% of the total variance. More specifically, the first component is a good proxy for soil-related extreme events, while the second one closely relates to population-related extreme events, as discussed above. Table 1 hereafter summarise the variables used in our econometric analysis, how they are measured and the related data sources.

[7] We still present variables excluded from the empirical analysis in the Appendix, for descriptive purposes.

Figure 1. Results of principal component analysis (PCA) for automation innovation and extreme climate events



Notes: Authors' own computations based on OECD REGPAT data and OECD data on climate hazards. Cut-off threshold taken to determine the number of components is eigenvalues > 1.

Table 1. Variables description, computation details and sources

Variable	Level	Measure	Data source
Dependent variables			
Long-term unemployment	Individual	Dummy = 1 if unemployment duration is > 1 year, 0 otherwise	Eurostat's LFS
Unemployment	Individual	Dummy = 1 if unemployed, 0 otherwise	Eurostat's LFS
Inactivity	Individual	Dummy = 1 if inactive, 0 otherwise	Eurostat's LFS
Megatrend - digitalisation			
Automation adoption	Country	Stock of imports in advanced manufacturing technologies (industrial robots, additive manufacturing, internet-of-things) over total employment, measured in log	Eurostat's Comext
Automation innovation	Country	Principal component computed using data on the cumulated number of patent applications in ICTs, AI, additive manufacturing, and nanotechnologies	OECD REGPAT
Megatrend - globalisation			
Total GVC participation	Country	Sum of forward and backward GVC participation	OECD TiVa
Trade openness	Country	Sum of total imports and exports over GDP, measured in %	World Bank
FDI openness	Country	Sum of inward and outward FDI over GDP, measured in %	World Bank
Megatrend - climate change			
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)	OECD 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)	OECD database on climate hazards
CO_2 emissions	Country	Total number of tonnes of CO_2 produced, measured in log	OECD database on climate hazards
Megatrend - demographic change			
Population share > 65 years	Country	Share of individuals aged above 65 years in total population, measured in %	OECD/Eurostat statistics
Fertility rate	Country	Number of children per woman, measured in log	OECD/Eurostat statistics
Net migration rate	Country	Difference between inflows of migrants and outflows of expatriates over total population, measured in %	OECD/Eurostat statistics
Controls			
Gender	Individual	Dummy = 1 if female, 0 if male	Eurostat's LFS

Age group	Individual	Ordinal variable ranging from 1 to 12, corresponding to 5-year age bands going from age 15-19 to age 70-74	Eurostat's LFS
Educational attainment	Individual	Ordinal variable ranging from 1 to 8, corresponding to ISCED-1/8 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 urbanisation	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
Real GDP	Country	Real GDP in millions LCU, measured in log	World Bank
R&D expenditure	Country	Share of R&D expenditure in GDP, measured in %	World Bank
Agricultural sector	Country	Share of agricultural sector value added in GDP, measured in %	World Bank
Manufacturing sector	Country	Share of manufacturing sector value added in GDP, measured in %	World Bank
Service sector	Country	Share of service sector value added in GDP, measured in %	World Bank

3.3. Econometric specification

Our main empirical exploration focuses on long-term unemployment outcome, while in the Appendix we further investigate how megatrends affect inactivity. In the first step of our econometric analysis, we estimate a probit regression model, where we explain changes in the probability of individuals falling into long-term unemployment because of aggregate megatrends. However, a standard probit model comparing long-term unemployed individuals to all other individuals in the active population may lead to biased estimates. In fact, such individuals are likely to be affected by a selection mechanism for which they first fall into unemployment, then protracted until they transit into long-term unemployment because of the worsening of their exclusion condition. To account for such potential selection bias, we estimate the sample selection correction model proposed by van de Ven and van Praag (1981), which is similar to Heckman's (1979) method, but designed to accommodate binary outcomes. This procedure helps us to purge estimates from the potential bias arising from unobservable factors leading some individual to become unemployed (or inactive) and achieve partial identification even in situations where proper exclusion restrictions are not easy to identify (Honoré and Hu, 2020; 2022). Specifically, we estimate a conditional mixed-process model following Roodman's (2011), combining a set of two reduced form equations:

$$\begin{cases} P\left(UNE_{i,c,r,t}=1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(LT_{i,c,r,t}=1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases} \quad (1)$$

where $UNE_{i,c,r,t}$ and $LT_{i,c,r,t}$ represent our main dependent variables, respectively in the first and second equation, identifying individual i in NUTS-2 region r = 1, …212 of country c = 1, …28 experiencing either unemployment (irrespective of its duration) or long-term unemployment at time t = 2009, …2019. As described in Table 1, $\boldsymbol{MT}_{c,t}$ represents a vector including all country-level variables capturing the four megatrends; $\boldsymbol{ILC}_{i,c,r,t}$ is a vector of individual-level controls capturing all most relevant characteristics common to both active and inactive individuals that may influence the probability of labour market exclusion; $\boldsymbol{CLC}_{c,t}$ is a vector including a range of country-level characteristics capturing the overall size of the economy, its sectoral composition, and its overall level of innovation activity (broadly defined by R&D expenditure). We further include region fixed effects (FE) to account for unobserved heterogeneity at the regional level (i.e., ϑ_r), capturing differences in the institutional and policy setting, and labour market features such as training policies and decentralised collective agreements. Similarly, we include time FE to account for common trends (i.e., τ_t) characterising all individuals and countries in our sample, such as the average level of technological progress, and the cost of capital.

The first equation computes the probability of an individual being unemployed against all active population, and represents the first stage (i.e., the selection process). Conversely, the second equation, conditional on being unemployed, estimates the probability of being long-term unemployed against that of being short-term and mid-term unemployed. By jointly estimating the two equations, the coefficients resulting from the second equation account for the factors that might create a selection bias in the probability of being long-term unemployed.

Our econometric strategy addresses endogeneity concerns by accounting for the potential selection mechanisms, which may lead to biased estimates. Furthermore, by research design, the difference in the unit of analysis between individuals' unemployment outcome and country-level factors makes it hard to conceive any mechanism leading to potential reverse-causality or simultaneity bias. One could still argue that some of the key explanatory variables measuring megatrends might capture indirect effects of other variables. For instance, some of the effect of digitalisation on unemployment may appear through globalisation or demographic changes, as discussed in Section 2. However, this should not be the case in our analysis since we account for all these factors simultaneously and by means of sets of different variables capturing as thoroughly as possible different aspects of each megatrend (e.g., adoption and innovation aspects of technological change, GVC participation, trade openness, and FDIs as aspects of globalisation, etc.).

Additionally, the high granularity of the individual-level controls capturing a large set of demographic characteristics, the number of country-level factors we control for beyond megatrends, and the sets of FE we include in all our specifications make it difficult for our estimates to be affected by omitted variable bias. Notwithstanding, we acknowledge that we do not control for important institutional factors such as retirement schemes, product market regulations, employment protection legislation and other policy tools that might affect the probability of individuals to fall in unemployment or inactivity, as such analysis falls out of our scope. Specifically, our estimates could be biased if such institutional factors would correlate with any monotonous trend in our megatrend variables (e.g., a raise in employment protection legislation in a country goes hand in hand with a similar increase in the level of automation adoption). In such a case, we might not rule out the possibility that our megatrend results are capturing the effect of changes in the policy.

In the second step of our analysis, we investigate the potential heterogeneity in the effect of megatrends on the probability of long-term unemployment across demographic characteristics of individuals (i.e., gender, age group, and educational attainment). Specifically, we run sets of three systems of equations as in Eq. (1) by implementing the interaction terms between each megatrend variable (one-by-one) and demographic characteristic in the second, as follows:

$$\begin{cases} P\left(UNE_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \boldsymbol{\beta_2 ILC}_{i,c,r,t} + \boldsymbol{\beta_3 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(LT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \beta_2 MT_{c,t} \times Gender_{i,c,r,t} + \boldsymbol{\beta_3 ILC}_{i,c,r,t} + \\ \qquad + \boldsymbol{\beta_4 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases}$$

$$\begin{cases} P\left(UNE_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \boldsymbol{\beta_2 ILC}_{i,c,r,t} + \boldsymbol{\beta_3 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(LT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \beta_2 MT_{c,t} \times Age\_group_{i,c,r,t} + \boldsymbol{\beta_3 ILC}_{i,c,r,t} + \\ \qquad + \boldsymbol{\beta_4 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases} \tag{2}$$

$$\begin{cases} P\left(UNE_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \boldsymbol{\beta_2 ILC}_{i,c,r,t} + \boldsymbol{\beta_3 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(LT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta_1 MT}_{c,t} + \beta_2 MT_{c,t} \times Education_{i,c,r,t} + \boldsymbol{\beta_3 ILC}_{i,c,r,t} + \\ \qquad + \boldsymbol{\beta_4 CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases}$$

Finally, we complement the main analysis by estimating supplementary probit and multivariate probit models to consider additional potential aspects distinguishing long-term unemployed individuals from the rest of the active population, as well as to test the robustness of our main results. Furthermore, as anticipated above, we estimate probit models and sample selection models analysing the effect of megatrends on changes in the probability of falling into inactivity, specifically focusing on those inactive individuals who are not actively seeking employment although being able to work (e.g., excluding permanently disable individuals). Model details and the related results are discussed in the Appendix.

4. Descriptive evidence

4.1. Stylised facts on employment, unemployment and inactivity

We start our exploration of the European labour market characteristics and the in-depth analysis of long-term unemployment and inactivity by discussing general statistics from the whole sample of about 29 million individuals we retrieved from LFS microdata. Tables 2 and 3 describe the distribution of employed, unemployed, and inactive population across years and European countries, respectively. The employed population across EU27 and the UK represents, on average, 64.8% of our sample based on age 15-64 (compared to 64.3% in official Eurostat's statistics), while total unemployed population ranges around 6.4% (in line with official statistics of about 6%). The remaining part of our sample, about 28.8%, represent inactive individuals (about 29.7% in official statistics). Overall, employment has increased steadily over the observation period up to the outbreak of the Covid-19 pandemic, rising from about a 62% share in 2009 to a 68% share in 2019. Conversely, the unemployment share has remained quite stable witnessing a slight raise from 6% in 2009 to about 8% in 2013, and then a decrease to 5% in 2019. The larger drop over time, compensating 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. Looking at Table 3, the European labour market presents consistent heterogeneities in terms of the relative distribution of the population across the three categories. On average over the period, 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 as having the highest inactivity rates across Europe (above 37%). In addition, Table 4 explores the heterogeneity of these three population categories across age, gender, and education groups. Overall, aggregate statistics suggests that unemployment conditions predominantly affect younger cohorts (i.e., between age 20 and age 35), regard mostly male and less educated individuals. Conversely, inactivity mostly occurs at the top and bottom of the age distribution (i.e., amongst individuals between age 15 and 24, and in the 60-64 band), predominantly hits women, and low skilled people.

Table 2. Employment, unemployment, and inactivity of EU27 + UK (average across countries), by year

	Employed		Unemployed		Inactive		Total
Year	N	%	N	%	N	%	N
2009	1,679,969	0.62	158,508	0.06	851,969	0.32	2,690,446
2010	1,777,441	0.63	189,744	0.07	873,771	0.31	2,840,956
2011	1,664,272	0.63	185,037	0.07	813,309	0.31	2,662,618
2012	1,815,160	0.63	210,475	0.07	835,606	0.29	2,861,241
2013	1,753,711	0.63	210,512	0.08	800,422	0.29	2,764,645
2014	1,746,701	0.64	199,980	0.07	775,360	0.28	2,722,041
2015	1,725,711	0.65	179,896	0.07	747,108	0.28	2,652,715
2016	1,734,276	0.66	162,156	0.06	731,808	0.28	2,628,240
2017	1,703,000	0.67	139,804	0.06	682,483	0.27	2,525,287
2018	1,644,924	0.68	120,443	0.05	650,743	0.27	2,416,110
2019	1,579,068	0.68	106,601	0.05	619,962	0.27	2,305,631
Total	18,824,233	0.65	1,863,156	0.06	8,382,541	0.29	29,069,930

Notes: Authors' own computations based on LFS data.

Table 3. Employment, unemployment, and inactivity of EU27 + UK (average over time), by country

	Employed		Unemployed		Inactive		Total
Country	N	%	N	%	N	%	N
AT	950,850	0.73	40,800	0.03	313,442	0.24	1,305,092
BE	389,245	0.61	33,650	0.05	211,833	0.33	634,728
BG	135,565	0.71	10,946	0.06	45,706	0.24	192,217
CY	190,173	0.68	20,835	0.07	70,653	0.25	281,661
CZ	348,499	0.66	21,244	0.04	160,049	0.30	529,792
DE	2,010,389	0.75	89,510	0.03	594,509	0.22	2,694,408
DK	576,045	0.73	40,664	0.05	171,290	0.22	787,999
EE	123,133	0.67	11,523	0.06	50,177	0.27	184,833
ES	415,018	0.58	100,115	0.14	200,090	0.28	715,223
FI	131,425	0.70	10,776	0.06	45,908	0.24	188,109
FR	1,473,127	0.60	207,029	0.08	763,217	0.31	2,443,373
GR	894,685	0.53	213,498	0.13	571,677	0.34	1,679,860
HR	134,931	0.65	17,448	0.08	55,761	0.27	208,140
HU	1,017,971	0.58	94,440	0.05	652,666	0.37	1,765,077
IE	864,786	0.62	105,286	0.08	423,478	0.30	1,393,550
IT	2,239,700	0.56	257,400	0.06	1,530,120	0.38	4,027,220
LT	301,652	0.67	32,545	0.07	118,120	0.26	452,317
LU	103,136	0.64	4,656	0.03	54,312	0.34	162,104
LV	131,166	0.68	18,266	0.10	42,146	0.22	191,578
MT	108,223	0.65	5,819	0.04	51,679	0.31	165,721
NL	496,564	0.77	27,317	0.04	118,337	0.18	642,218
PL	1,393,673	0.67	121,039	0.06	575,614	0.28	2,090,326
PT	698,687	0.63	94,843	0.09	317,859	0.29	1,111,389
RO	1,002,578	0.64	62,915	0.04	492,524	0.32	1,558,017
SE	1,587,130	0.77	124,328	0.06	357,736	0.17	2,069,194
SI	289,433	0.70	24,675	0.06	97,905	0.24	412,013
SK	412,595	0.66	46,635	0.08	162,480	0.26	621,710
UK	403,854	0.72	24,954	0.04	133,253	0.24	562,061
Total	18,824,233	0.65	1,863,156	0.06	8,382,541	0.29	29,069,930

Notes: Authors' own computations based on LFS data.

Table 4. Employment, unemployment, and inactivity of EU27 + UK (average across countries and over time), by age, gender, education

	Employed		Unemployed		Inactive		Total
	N	%	N	%	N	%	N
Panel A: Age							
15-19	377,730	0.15	118,679	0.05	2,043,133	0.80	2,539,542
20-24	1,193,527	0.48	291,646	0.12	1,016,361	0.41	2,501,534
25-29	1,742,694	0.71	254,873	0.10	442,274	0.18	2,439,841
30-34	2,029,301	0.77	212,653	0.08	383,885	0.15	2,625,839
35-39	2,339,964	0.80	206,103	0.07	392,439	0.13	2,938,506
40-44	2,598,896	0.81	204,916	0.06	412,276	0.13	3,216,088
45-49	2,703,923	0.80	198,356	0.06	467,043	0.14	3,369,322
50-54	2,601,985	0.77	175,440	0.05	593,827	0.18	3,371,252
55-59	2,165,995	0.67	143,686	0.04	931,717	0.29	3,241,398
60-64	1,070,218	0.38	56,804	0.02	1,699,586	0.60	2,826,608
Panel B: Gender							
Male	10,020,701	0.70	978,563	0.07	3,272,710	0.23	14,271,974
Female	8,803,532	0.59	884,593	0.06	5,109,831	0.35	14,797,956
Panel C: Education							
ISCED1	699,561	0.40	276,922	0.16	754,034	0.44	1,730,517
ISCED2	2,448,089	0.58	475,020	0.11	1,307,349	0.31	4,230,458
ISCED3	8,762,256	0.65	757,327	0.06	4,049,911	0.30	13,569,494
ISCED4	1,443,459	0.79	73,394	0.04	305,453	0.17	1,822,306
ISCED5	3,616,331	0.73	170,843	0.03	1,180,477	0.24	4,967,651
ISCED6	1,610,916	0.69	92,274	0.04	614,753	0.27	2,317,943
ISCED7	227,443	0.56	16,539	0.04	164,919	0.40	408,901
ISCED8	16,178	0.71	837	0.04	5,645	0.25	22,660
Total	18,824,233	0.65	1,863,156	0.06	8,382,541	0.29	29,069,930

Notes: Authors' own computations based on LFS data.

Focusing on unemployment patterns, Tables 5 shows the composition of unemployed population across European countries, between 2009 and 2019 and distinguishing between different durations. First, we observe that long-term unemployment (duration > 1 year) accounts for about 45.3% of total unemployment (in line with official statistics of about 43.2%). Conversely, short-term unemployment mostly relates to individuals experiencing lack of a job for less than six months (38%). 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 rising again to 41% in 2019. Conversely, long-term unemployment experienced an inverse pattern characterised by a steep increase from 33% in 2009 to 50% in 2014, and then a slight drop to 44% in 2019. At the same time, unemployment conditions of intermediate duration (i.e., 6-12 months) have steadily decreased over time, from 20% in 2009 to 15% in 2016, then remaining constant until 2019. Looking at cross-country differences, Table 6 highlight a strong heterogeneity in average unemployment duration (on average over the observation period). Unemployment conditions mostly concerned short-term outcomes in countries such as Austria, Denmark, Finland, Luxembourg, Sweden, and the UK, while countries featuring the highest exposure to labour market exclusion associated with long-term unemployment were Bulgaria, Greece, Hungary, Ireland, Italy, Portugal, and Slovakia.

Table 5. Unemployment across EU27 + UK (average across countries), by year and duration

	< 6 months		6-11 months		> 1 year		Total
Year	N	%	N	%	N	%	N
2009	73,784	0.47	32,027	0.20	52,697	0.33	158,508
2010	75,489	0.40	38,041	0.20	76,214	0.40	189,744
2011	71,187	0.38	32,850	0.18	81,000	0.44	185,037
2012	78,138	0.37	36,744	0.17	95,593	0.45	210,475
2013	73,795	0.35	35,687	0.17	101,030	0.48	210,512
2014	67,851	0.34	31,479	0.16	100,650	0.50	199,980
2015	62,177	0.35	28,021	0.16	89,698	0.50	179,896
2016	58,505	0.36	24,279	0.15	79,372	0.49	162,156
2017	52,329	0.37	20,971	0.15	66,504	0.48	139,804
2018	47,519	0.39	18,003	0.15	54,921	0.46	120,443
2019	43,747	0.41	16,226	0.15	46,628	0.44	106,601
Total	704,521	0.38	314,328	0.17	844,307	0.45	1,863,156

Notes: Authors' own computations based on LFS data.

Table 6. Unemployment across EU27 + UK (average over time), by country and duration

	< 6 months		6-11 months		> 1 year		Total
Country	N	%	N	%	N	%	N
AT	22,946	0.56	7,341	0.18	10,513	0.26	40,800
BE	11,864	0.35	5,249	0.16	16,537	0.49	33,650
BG	2,652	0.24	1,710	0.16	6,584	0.60	10,946
CY	9,616	0.46	3,904	0.19	7,315	0.35	20,835
CZ	9,375	0.44	4,334	0.20	7,535	0.35	21,244
DE	37,065	0.41	13,498	0.15	38,947	0.44	89,510
DK	26,610	0.65	6,719	0.17	7,335	0.18	40,664
EE	5,066	0.44	1,847	0.16	4,610	0.40	11,523
ES	38,788	0.39	17,306	0.17	44,021	0.44	100,115
FI	7,074	0.66	1,378	0.13	2,324	0.22	10,776
FR	84,343	0.41	38,689	0.19	83,997	0.41	207,029
GR	48,772	0.23	28,663	0.13	136,063	0.64	213,498
HR	5,062	0.29	2,807	0.16	9,579	0.55	17,448
HU	33,312	0.35	20,093	0.21	41,035	0.43	94,440
IE	32,874	0.31	17,682	0.17	54,730	0.52	105,286
IT	79,239	0.31	35,747	0.14	142,414	0.55	257,400
LT	12,521	0.38	6,614	0.20	13,410	0.41	32,545
LU	2,407	0.52	883	0.19	1,366	0.29	4,656
LV	6,536	0.36	3,635	0.20	8,095	0.44	18,266
MT	2,100	0.36	763	0.13	2,956	0.51	5,819
NL	12,486	0.46	4,707	0.17	10,124	0.37	27,317
PL	51,809	0.43	24,953	0.21	44,277	0.37	121,039
PT	30,188	0.32	14,848	0.16	49,807	0.53	94,843
RO	24,725	0.39	11,646	0.19	26,544	0.42	62,915
SE	75,943	0.61	23,276	0.19	25,109	0.20	124,328
SI	8,431	0.34	4,481	0.18	11,763	0.48	24,675
SK	9,573	0.21	7,286	0.16	29,776	0.64	46,635
UK	13,144	0.53	4,269	0.17	7,541	0.30	24,954
Total	704,521	0.38	314,328	0.17	844,307	0.45	1,863,156

Notes: Authors' own computations based on LFS data.

Table 7. Unemployment across EU27 + UK (average across countries and over time), by age, gender, education and duration

	< 6 months		6-11 months		> 1 year		Total
	N	%	N	%	N	%	N
Panel A: Age							
15-19	77,163	0.65	20,099	0.17	21,417	0.18	118,679
20-24	136,154	0.47	52,576	0.18	102,916	0.35	291,646
25-29	103,605	0.41	45,108	0.18	106,160	0.42	254,873
30-34	78,481	0.37	36,983	0.17	97,189	0.46	212,653
35-39	71,452	0.35	35,143	0.17	99,508	0.48	206,103
40-44	67,608	0.33	33,472	0.16	103,836	0.51	204,916
45-49	62,673	0.32	31,831	0.16	103,852	0.52	198,356
50-54	52,213	0.30	27,685	0.16	95,542	0.54	175,440
55-59	39,308	0.27	22,274	0.16	82,104	0.57	143,686
60-64	15,864	0.28	9,157	0.16	31,783	0.56	56,804
Panel B: Gender							
Male	366,943	0.37	167,101	0.17	444,519	0.45	978,563
Female	337,578	0.38	147,227	0.17	399,788	0.45	884,593
Panel C: Education							
ISCED1	103,320	0.37	48,742	0.18	124,860	0.45	276,922
ISCED2	175,429	0.37	83,383	0.18	216,208	0.46	475,020
ISCED3	283,659	0.37	127,463	0.17	346,205	0.46	757,327
ISCED4	28,253	0.38	12,252	0.17	32,889	0.45	73,394
ISCED5	67,831	0.40	26,563	0.16	76,449	0.45	170,843
ISCED6	37,737	0.41	13,593	0.15	40,944	0.44	92,274
ISCED7	7,915	0.48	2,206	0.13	6,418	0.39	16,539
ISCED8	377	0.45	126	0.15	334	0.40	837
Total	704,521	0.38	314,328	0.17	844,307	0.45	1,863,156

Notes: Authors' own computations based on LFS data.

Beyond aggregate figures, we find significant heterogeneity in unemployment duration also across age groups, gender, and educational attainment. Table 7 highlights a consistent polarisation of short-term and long-term unemployment across individuals of different ages. Specifically (Panel A), younger individuals mostly experienced short periods without a job (i.e., about 65% of individuals aged 15-19, 47% of individuals aged 20-24); conversely, long-term unemployment is the highest across older individuals (i.e., on average, 56% of individuals aged 50-64). While we do not uncover any substantial difference in the distribution of unemployment outcomes of different duration between males and females (Panel B), we find some heterogeneity looking at differences in the level of education (Panel C): short-term unemployment outcomes were mostly experienced by highly educated individuals (i.e., on average 43% across ISCED-5/8 levels), whereas protracted unemployment periods were, on average, equally important for low-educated and middle-educated people (i.e., 45% of total unemployed individuals both across ISCED-1/2 and ISCED-3/4 levels).

4.2. Stylised facts on megatrends

Hereafter, we briefly discuss the main dynamics and trends characterising digitalisation, globalisation, climate, and demographic changes. A detailed description of all variables discussed in Section 3 (Table 1) and capturing these four megatrends is reported in the Appendix. Table 8 below presents summary statistics, correlations, and VIF values for our main explanatory variables.

Table 8. Summary statistics: correlation, variance inflation factors, and summary statistics of the main explanatory variables

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]
Digitalisation											
[1] Automation adoption (stock of AMT imports)	1.00										
[2] Automation innovation (patents, PCA)	0.27	1.00									
Globalisation											
[3] Total GVC participation	0.60	-0.33	1.00								
[4] Trade openness	0.56	-0.41	0.85	1.00							
[5] FDI openness	-0.14	-0.16	0.05	0.13	1.00						
Climate change											
[6] Extreme climate events 1 (soil-related, PCA)	-0.31	-0.07	-0.33	-0.27	-0.04	1.00					
[7] Extreme climate events 2 (people-related, PCA)	-0.20	0.03	-0.10	-0.16	-0.01	0.17	1.00				
[8] CO_2 emissions	-0.07	0.78	-0.42	-0.62	-0.22	0.02	0.23	1.00			
Demographic change											
[9] Population share > 65 years	-0.07	0.25	-0.37	-0.40	-0.44	0.12	0.16	0.21	1.00		
[10] Fertility rate	0.22	0.36	-0.09	-0.09	-0.10	-0.15	-0.21	0.16	-0.08	1.00	
[11] Net migration rate	0.56	0.11	0.46	0.56	0.19	-0.11	-0.21	-0.22	-0.21	-0.08	1.00
VIF	3.64	6.27	5.16	7.04	1.53	1.26	1.28	5.47	1.83	1.51	2.37
Mean	14.12	-0.89	52.61	125.54	20.72	-0.29	-0.30	3.88	15.11	0.44	0.24
S.D.	0.98	1.75	8.76	66.98	77.24	1.24	1.36	1.42	1.84	0.12	0.59
Min	12.08	-3.01	33.48	45.42	-86.59	-3.26	-2.31	0.30	9.91	0.15	-0.92
Max	16.97	3.90	77.15	382.35	581.41	3.41	3.33	6.64	18.74	0.72	2.32

Notes: Authors' own computation.

4.2.1. Digitalisation trends

The digitalisation process of European economies has steadily grown over the decade 2009-2019. This has happened both in terms of adoption of new advanced manufacturing technologies (i.e., industrial robots, additive manufacturing, and internet-of-things), as well as in terms of innovation in the field of advanced automation (primarily, in AI). Looking at the adoption side of digitalisation (Tables A.1 and A.2 in the Appendix), European countries display a robust growth in terms of both import and production stocks of advanced technologies, growing respectively by 59% and 96.3% in absolute terms (as measured by imports/production per person employed). Similarly, exports of these technologies grown by about 95.8%, on average, over the observation period. Looking at cross-country differences, while aggregate production stock remains constrained to few countries due to the presence of local firms (e.g., Austria, Germany, Denmark, France, and Italy to mention major producers), all European economies witnessed substantial, yet heterogeneous, import stocks (e.g., the Netherlands, Malta, Hungary, Luxembourg, and Belgium just to mention major importers but non-producing countries). Coherently with these patterns, adoption stocks (i.e., net consumption = imports + production – exports) have grown by about 70% in absolute terms, between 2009 and 2019. As discussed by Castellani et al., (2022), while several EU27 economies are characterised by import-export patterns – still, remaining net importers, hance adopters of these technologies – those featuring the highest net consumption mostly correspond to producing countries like Germany, Denmark, Italy, and Sweden. This emphasises the role of local innovation hubs in boosting actual technology adoption.

Similar trends also emerge if looking at the innovation side of digitalisation (Tables A.3 and A.4 in the Appendix). ICTs, additive manufacturing, and AI (with the notable exception of nanotechnologies) have all experienced growing innovation activity – in terms of the number of yearly patent applications at the EPO, i.e., the flow – between 2009 and 2019, respectively growing by around 30%, 150%, and 151% in absolute terms. As much as production patterns, cross-technology patenting activity mostly concentrates in few highly innovative countries: Germany, France, the UK, and to a lower extent Sweden, Finland, Spain, the Netherlands, and Italy lead the technological progress of the region.

4.2.2. Globalisation trends

Moving on to globalisation trends (Tables A.5 and A.6 in the Appendix), Europe's total GVC participation (i.e., forward + backward participation), on average, shows a stable pattern over our observation period, while trade openness has increased over time (+18%). Leading countries both in GVC participation and total trade openness are smaller countries such as Luxembourg, Ireland, and Malta, and more supply-chain-integrated economies (mostly, central-eastern European ones) like Hungary, Slovakia, Czech Republic. Conversely, FDI patterns across the continent have been more erratic both over time and across countries, potentially reflecting country-specific policy actions affecting inward and outward FDI flows. To further delve into the European globalisation landscape, Figures A.1, A.2, and A.3 in the Appendix present additional details on the relative positioning of each country between components of each globalisation measure (i.e., forward vs backward GVC participation, total imports vs total exports, and inward vs outward FDIs).

4.2.3. Climate change trends

Our exploration of climate change patterns starts by recognising that these phenomena are multifaceted, and therefore need to be addressed by looking at different components. Soil-related extreme climate events (Figure A.4 in the Appendix) describe, on average between 2009 and 2019, a picture of growing droughts in the northern European area and a severe situation in southern countries like Italy and Greece. Important levels of land exposure to very heavy precipitation events of short duration (< 1 week) have characterised mostly north and central-eastern European countries, above all Germany, the Netherlands, and Baltic countries. Conversely, extreme precipitation events of longer duration – hence, having more severe effects – between 1 and 2 weeks hit mostly southern countries such as Italy, Slovenia, Croatia, and Greece. In particular, the combination of severe drought periods and prolonged extreme precipitation events creates critical conditions and increases the risk of natural disasters, like the one hitting the Emilia-Romagna region in Italy, in May 2023.

Population-related extreme climate events, on average, have affected mostly western and Balkan countries (Figure A.5 in the Appendix). Specifically, exposure to hot days has prominent in Hungary, Croatia, Romania, as well as in France and Greece. Over the last decades, unprecedented tropical nights have been a growing issue for Germany, and for central-eastern European countries like Hungary and Poland, but a minor phenomenon across Mediterranean countries. Finally, population exposure to extreme icing days mostly concentrates in western countries facing the Northern Sea, such as the UK, the Netherlands, Belgium, Germany, and Denmark.

Looking at more traditional measures of climate change (Figure A.6 in the Appendix), CO_2 emissions clearly appear to go together with economic and industrial development: western European countries are, on average, those featuring highest emission levels (Germany, above all). Yet, data on mortality levels from exposure to pollutants (i.e., PM2.5, lead, ozone, and radon) highlights a significant concentration of such deaths in central-eastern countries such as Bulgaria, Romania, Hungary, and Poland. This is partially due to differences in regulation and their enforcement (e.g., lower level of workers' health protection, environmental safety, and protection laws) in these countries, as compared to other EU member states (Feng et al., 2020; Chen et al., 2021).

4.2.4. Demographic change trends

Finally, we delve into the heterogeneity in demographic patterns across EU27 and the UK (Table A.7 in the Appendix). Such heterogeneity mostly relates to cross-country differences, since demographic characteristics such as population composition, fertility rates, and life expectancy are highly persistent over time. Population aging (share of population aged 65+) clearly appears as an important phenomenon in Mediterranean countries like Italy, Portugal, Greece, and in central European countries like Germany. Conversely, most central-eastern EU countries (e.g., Czech Republic, Slovakia, Poland, and Hungary) feature amongst youngest countries, with the largest share of the population located in the age 15-65 band. Notably, amongst countries with the highest share of youths below age 15 we note Ireland, the UK and France. In fact, these three countries (and Sweden) also display the highest fertility rates amongst all European countries analysed here, whereas all Mediterranean countries (i.e., Spain, Portugal, Greece, Malta, Cyprus, Italy) and Poland rank the lowest. Furthermore, despite central-eastern EU countries and Baltic countries largely benefitted over the past decades from their integration into the EU block in terms of several socio-economic dimensions, life expectancy still ranks the lowest across this group, led by Latvia, Lithuania, and Bulgaria.

The only demographic dimension worth analysing over time is migration (see the last two columns of Table A.7 in the Appendix). We compare cross-country net migration rates in the three-year period 2009-2011 and in the 2017-2019 period. On average, during the period after the 2008's global financial crisis, Europe has become more recipient of migrants (+85% in net migration rate). However, only few EU economies have experienced an increasing net immigration: above all Malta, followed by a consistent group experiencing moderate or little growth (i.e., Austria, Germany, Denmark, Spain, Hungary, the Netherlands, Sweden, and Slovenia). A sizeable part of the average growth in immigration rates across the region comes from a consistent slowdown of emigration rates from Lithuania, Latvia, Romania, and to a reversal from being net 'exporters' to net 'importers' of migrants for Estonia, Ireland, and (to a lower extent) Portugal, and Slovakia. Similarly, countries like the UK (during our observation period, still part of the EU) and Italy – frequently pushing for more restrictive immigration EU policies – experienced decreasing net immigration rates over time.

5. Econometric results

5.1. Main results

Table 9 presents the results of the probit model defined by Eq. (1) in Section 3.3, showing changes in the predicted probability of long-term unemployment associated with megatrends. We report coefficients as average marginal effects (AME) and we compute standard errors clustered at the NUTS-2 region level to account for the heterogeneous effect that megatrends might have across different regions within each country (e.g., droughts in Italy, hitting more severely southern rather than northern regions). Furthermore, we report both unweighted (columns (1) and (2)) and weighted (columns (3) and (4)) estimates, the latter computed using sampling weights provided in Eurostat's LFS.[8] Results for the first stage of the sample selection model in columns (1), which model the selection process leading to the unemployment outcome, highlight that both digitalisation and demographic changes exert a negative and significant (5% to 1% level) effect on changes in the probability of being unemployed. Specifically, a 10% increase in the adoption of automation technologies (i.e., as measured by the stock of imports in advanced manufacturing technologies) comes with a 0.19 percentage point (p.p.) drop in the probability of being unemployed, while a 10% increase in the variables capturing demographic changes (i.e., population aging, fertility rates, and migration rates) relates to a drop of between 0.09 p.p. and 1.23 p.p., with fertility rates mainly driving the effect of demographic changes. These effects are qualitatively and statistically similar to those reported in column (3) for weighted estimates, although we underscore that the role played by digital technologies is slightly bigger in magnitude and that of demographic changes turns out slightly smaller when using sampling weights.

In columns (2) and (4) we present AMEs of megatrend variables for the second stage of the sample selection model, specifically focusing on long-term unemployment. Conditional on being unemployed, our results highlight that digitalisation exerts an opposite effect on individuals facing labour market exclusion. We observe a significant (5% level) positive effect digital innovations on the probability of falling into protracted unemployment. Indeed, a 10% increase in automation-related patenting leads to an increase of long-term unemployment probability of about 0.12 p.p. in the case of unweighted regressions (column (2)), doubling to 0.24 p.p. in weighted models. These findings support our expectations on the role of

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[8] 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 every individual in the sample is representative of the true full population in the same way. This is frequently not the case and most large-scale survey provide sampling weights to account for such differences in the individual representativeness.

digitalisation trends on labour market exclusion, as discussed in Section 2.1. In column (2), we also find a significant (5% level) positive effect of globalisation, as measured by trade openness, on the probability of being long-term unemployed, which is very small in magnitude and only appears in unweighted estimates. Specifically, a 10% increase in the level of trade openness brings a 0.02 p.p. raise in the exclusion probability. This additional finding partially supports our expectation on the role of globalisation, discussed in Section 2.2.[9]

5.2. Moderating effect of demographic characteristics

We now explore results from the estimation of the three sets of reduced form equations in Eq. (2), where we explore how the average effects of megatrends uncovered in Table 9 are moderated by demographic characteristics such as gender, age group, and educational attainment. To reduce computational complexity, we take the model estimated in columns (1) and (2) of Table 9 (i.e., the unweighted sample selection model) as reference model to explore such heterogeneity. Results are reported in Table 10. Although we still include all megatrends, individual-/country-level controls, and FE, we only present AMEs for how each megatrend (one-by-one) specifically affect demographic groups.

Columns (1) and (2) explore moderations for our digitalisation variables. The adoption of automation technologies – on average, not significant – is instead found to significantly (10 to 5% level) reduce the probability of long-term unemployment for highly educated individuals (i.e., ISCED 5-7). Conversely – and coherently with our main results –, patenting activity on automation technologies raises long-term unemployment across all demographic categories. Specifically, we find male individuals to be mostly exposed, together with older individuals between age 55 and 64, and less educated people (i.e., ISCED 1-2). Indeed, findings on the role of age and education as moderators in the relationship between digitalisation and the probability of long-term unemployment are coherent with the literature (e.g., Olsson and Tåg, 2017; Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Schmidpeter and Winter-Ebmer, 2021) and with our expectations, discussed in Section 2.1.

Looking at the heterogeneity in the role of globalisation (columns (3) to (5)), we find that GVC participation does not exert any effect across demographic groups, coherently with our main estimates on its average marginal effect. Conversely, we find trade openness to mainly affect the probability of long-term unemployment for males, younger and middle-aged workers (i.e., age 20 to 54), and – to a lower

[9] 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 do not highlight any country to be a main driver in our results. They are available upon request from the authors.

extent – less educated individuals (i.e., ISCED 1). Additionally, we find some heterogeneity across all three demographic characteristics in the effect of FDI openness – on average, not statistically significant – which is however negligible in magnitude. As discussed in Section 2.2, these findings are coherent with theory suggesting that the growing functional specialisation featured by developed economies disproportionally affect individuals in manufacturing activities (mainly, males) and those with lower educational attainment.

Climate change variables (i.e., extreme climate events) and CO_2 emissions (columns (6) to (8)) also present some heterogeneity across demographic groups, despite being all not significant on average in our main estimates in Table 9. Both extreme climate event variables (columns (6) and (7)) appear to negatively affect the probability of long-term unemployment for male individuals. Furthermore, soil-related events increase labour market exclusion for younger individuals (i.e., age 15 to 24), while they reduce it for older (i.e., age 45 to 64) and less educated people (i.e., ISCED 1-2). Conversely, people-related events negatively affect exclusion chances for middle-aged individuals, although such effect is very small and only slightly significant (10% level). Overall, we find CO_2 emissions to have no significant effect across all demographic groups, confirming our main results. These findings on the role of climate changes are broadly in line with our expectations of a negative relationship with labour market exclusion. Nonetheless, these should be considered cautiously since such effects only emerge for some demographic groups (and not on average), and (above all) because extreme climate event variables are likely to capture more complex short-run mechanisms associated with *laissez-faire* approaches towards climate change mitigation, leading to higher economic growth and, in turn, to lower risks of exclusion.

Finally, we uncover some heterogeneity also concerning demographic change measures in columns (9) to (11). While aging – as measured by the share of elder population above age 65 – exerts no significant effect on any demographic group, fertility rates decrease the probability of long-term unemployment for women and individuals across most levels of education, except those in higher levels (i.e., ISCED 7-8). Furthermore, we observe a positive effect of net migration rates on long-term unemployment probabilities for older individuals (i.e., age 55 to 64); instead, a negative effect emerges for higher educated people, although with limited statistical significance. These findings on the short-run effect of demographic changes on labour market exclusion mostly goes against our expectations, discussed in Section 2.4. However, we underscore that the average effect of demographic changes found in Table 9 remains negligible from a statistical standpoint, hence these findings on the moderating role of demographic characteristics should be considered prudently, as they may be affected by individual characteristics or may capture specific characteristics of the labour market not considered in this study.

Table 9. Main results: probit model of long-term unemployment and exposure to megatrends with sample selection, conditional mixed-process estimator

	Unweighted estimates		Weighted estimates using sampling weights	
	(1)	(2)	(3)	(4)
	1st stage: Unemployed vs Active	2nd stage: LT vs ST unemployed	1st stage: Unemployed vs Active	2nd stage: LT vs ST unemployed
[1] Automation adoption	-0.019**	-0.017	-0.030**	0.023
	(0.009)	(0.042)	(0.013)	(0.020)
[2] Automation innovation	-0.002	0.012**	-0.004	0.024**
	(0.002)	(0.006)	(0.003)	(0.011)
[3] Total GVC participation	-0.000	-0.001	-0.000	0.004
	(0.001)	(0.003)	(0.001)	(0.003)
[4] Trade openness	0.000	0.002**	-0.000	0.001
	(0.000)	(0.001)	(0.000)	(0.001)
[5] FDI openness	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
[6] Extreme climate events 1	-0.000	-0.002	0.000	-0.003
	(0.001)	(0.002)	(0.001)	(0.002)
[7] Extreme climate events 2	0.000	-0.003	0.001	0.000
	(0.001)	(0.003)	(0.001)	(0.003)
[8] CO_2 emissions	0.030*	-0.045	0.024*	-0.067
	(0.016)	(0.067)	(0.014)	(0.054)
[9] Pop. share > 65 years	-0.009**	-0.010	-0.002	-0.002
	(0.005)	(0.017)	(0.007)	(0.009)
[10] Fertility rate	-0.123***	-0.090	-0.071***	0.040
	(0.023)	(0.201)	(0.026)	(0.089)
[11] Net migration rate	-0.019***	0.009	-0.019***	0.012
	(0.006)	(0.029)	(0.006)	(0.016)

Observations	2,059,993	184,137	2,059,993	184,137
Individual characteristics	YES		YES	
Country-level controls	YES		YES	
Region (NUTS-2) FE	YES		YES	
Year FE	YES		YES	

Notes: Reported coefficients are average marginal effects. Robust standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (1) and (2), linearized standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (3) and (4). Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). All models are estimated using Roodman's (2011) `cmp` STATA command, following Van de Ven and Van Praag (1981) probit sample selection model, analogous to Heckman's (1979) method. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10. Heterogeneity in the relationship between megatrends and the probability of long-term unemployment across gender, age bands, and educational attainment

AME of [variable] for:	[1] Automation adoption	[2] Automation innovation	[3] Total GVC participation	[4] Trade openness	[5] FDI openness
	(1)	(2)	(3)	(4)	(5)
Panel A: Gender					
Male	-0.012	0.014*	0.001	0.002*	-0.000
	(0.026)	(0.008)	(0.003)	(0.001)	(0.000)
Female	-0.043	0.009	-0.002	0.002	-0.000**
	(0.028)	(0.007)	(0.003)	(0.001)	(0.000)
Panel B: Age					
Age 15-19	-0.035	0.015	-0.004	0.001*	-0.000
	(0.025)	(0.019)	(0.003)	(0.001)	(0.000)
Age 20-24	-0.034	0.010	-0.003	0.002**	-0.000**
	(0.027)	(0.010)	(0.003)	(0.001)	(0.000)
Age 25-29	-0.026	0.001	-0.000	0.002**	-0.000
	(0.030)	(0.006)	(0.002)	(0.001)	(0.000)
Age 30-34	-0.026	0.006	-0.001	0.002**	-0.000**
	(0.030)	(0.009)	(0.002)	(0.001)	(0.000)
Age 35-39	-0.021	0.004	-0.000	0.002**	-0.000
	(0.032)	(0.007)	(0.002)	(0.001)	(0.000)
Age 40-44	-0.009	0.009	-0.000	0.002*	-0.000
	(0.032)	(0.010)	(0.002)	(0.001)	(0.000)
Age 45-49	-0.007	0.012	-0.000	0.002*	-0.000
	(0.031)	(0.010)	(0.002)	(0.001)	(0.000)
Age 50-54	0.007	0.017	0.001	0.002*	-0.000
	(0.029)	(0.010)	(0.002)	(0.001)	(0.000)
Age 55-59	0.007	0.019**	-0.000	0.002	0.000
	(0.029)	(0.010)	(0.002)	(0.001)	(0.000)
Age 60-64	0.022	0.025**	0.002	0.002	0.001
	(0.028)	(0.010)	(0.003)	(0.001)	(0.000)
Panel C: Education					
ISCED 1	-0.020	0.017**	0.000	0.002*	-0.000
	(0.024)	(0.008)	(0.002)	(0.001)	(0.000)
ISCED 2	-0.015	0.015*	0.000	0.002	-0.000
	(0.020)	(0.008)	(0.002)	(0.001)	(0.000)
ISCED 3	-0.020	0.013	-0.000	0.001	-0.000**
	(0.015)	(0.009)	(0.002)	(0.001)	(0.000)
ISCED 4	-0.022	0.011	-0.001	0.001	-0.000

	(0.015)	(0.009)	(0.002)	(0.001)	(0.000)
ISCED 5	-0.029*	0.009	-0.002	0.001	-0.000***
	(0.016)	(0.010)	(0.003)	(0.001)	(0.000)
ISCED 6	-0.034*	0.002	-0.001	0.001	-0.000
	(0.018)	(0.007)	(0.002)	(0.001)	(0.000)
ISCED 7	-0.038**	-0.010	-0.001	0.001	-0.000**
	(0.018)	(0.009)	(0.002)	(0.001)	(0.000)
ISCED 8	-0.017	-0.003	-0.004	0.000	-0.002
	(0.026)	(0.025)	(0.007)	(0.001)	(0.002)

Notes: Reported coefficients are average marginal effects of megatrend variables, for each demographic group. Robust standard errors in parentheses (clustered at the NUTS-2 level). Unweighted estimates are based on the selection model from columns (1) and (2) of Table 6, augmented with interactions between megatrends and demographic characteristics as in Eq. (2). All models include megatrends, individual characteristics, country-level controls, region (NUTS-2) FE, and year FE. Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). All models are estimated using Roodman's (2011) `cmp` STATA command, following Van de Ven and Van Praag (1981) probit sample selection model, analogous to Heckman's (1979) method. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table 10. (continued) Heterogeneity in the relationship between megatrends and the probability of long-term unemployment across gender, age bands, and educational attainment

AME of [variable] for:	[6] Extreme climate events 1	[7] Extreme climate events 2	[8] CO_2 emissions	[9] Pop. share > 65 years	[10] Fertility rate	[11] Net migration rate
	(6)	(7)	(8)	(9)	(10)	(11)
Panel A: Gender						
Male	-0.007***	-0.010***	-0.054	-0.016	-0.081	0.016
	(0.002)	(0.003)	(0.060)	(0.016)	(0.101)	(0.033)
Female	0.004	0.005	-0.043	-0.006	-0.239***	-0.003
	(0.003)	(0.003)	(0.062)	(0.017)	(0.082)	(0.033)
Panel B: Age						
Age 15-19	0.019***	0.013	-0.005	-0.001	-0.112	0.017
	(0.006)	(0.008)	(0.054)	(0.012)	(0.079)	(0.031)
Age 20-24	0.013***	0.004	-0.026	-0.004	-0.138	-0.010
	(0.004)	(0.004)	(0.065)	(0.013)	(0.099)	(0.022)
Age 25-29	0.000	-0.005	-0.049	-0.010	-0.127	-0.030
	(0.004)	(0.004)	(0.068)	(0.013)	(0.117)	(0.019)
Age 30-34	0.002	-0.003	-0.046	-0.007	-0.113	-0.011
	(0.003)	(0.004)	(0.067)	(0.014)	(0.126)	(0.028)
Age 35-39	-0.003	-0.008*	-0.053	-0.009	-0.105	-0.014
	(0.003)	(0.004)	(0.065)	(0.015)	(0.130)	(0.031)
Age 40-44	-0.003	-0.008*	-0.049	-0.008	-0.084	0.021
	(0.003)	(0.005)	(0.064)	(0.015)	(0.130)	(0.034)
Age 45-49	-0.009**	-0.008*	-0.048	-0.008	-0.050	0.017

	(0.004)	(0.005)	(0.062)	(0.014)	(0.123)	(0.030)
Age 50-54	-0.012**	-0.002	-0.046	-0.007	0.009	0.035
	(0.005)	(0.005)	(0.059)	(0.015)	(0.114)	(0.028)
Age 55-59	-0.012**	-0.008	-0.047	-0.006	0.022	0.048**
	(0.006)	(0.007)	(0.056)	(0.014)	(0.104)	(0.024)
Age 60-64	-0.020**	0.007	-0.041	-0.004	-0.053	0.053**
	(0.009)	(0.005)	(0.053)	(0.013)	(0.123)	(0.024)
Panel C: Education						
ISCED 1	-0.005*	-0.004	-0.047	-0.014	-0.210***	0.000
	(0.003)	(0.005)	(0.058)	(0.013)	(0.071)	(0.017)
ISCED 2	-0.006**	-0.010**	-0.057	-0.017	-0.120	0.006
	(0.003)	(0.005)	(0.057)	(0.011)	(0.078)	(0.016)
ISCED 3	-0.001	-0.003	-0.049	-0.013	-0.159***	-0.009
	(0.002)	(0.003)	(0.053)	(0.010)	(0.053)	(0.012)
ISCED 4	0.004	-0.004	-0.053	-0.011	-0.203***	-0.013
	(0.003)	(0.005)	(0.051)	(0.010)	(0.071)	(0.010)
ISCED 5	0.006	0.009	-0.045	-0.002	-0.267**	-0.031*
	(0.004)	(0.006)	(0.051)	(0.012)	(0.121)	(0.016)
ISCED 6	0.003	0.005	-0.054	-0.009	-0.246**	-0.052*
	(0.003)	(0.006)	(0.052)	(0.010)	(0.114)	(0.028)
ISCED 7	0.018	0.008	-0.074	-0.003	-0.355	-0.041
	(0.011)	(0.011)	(0.052)	(0.012)	(0.221)	(0.029)
ISCED 8	0.006	-0.021	-0.030	-0.005	-0.305	-0.013
	(0.013)	(0.045)	(0.058)	(0.028)	(0.340)	(0.068)

Notes: Reported coefficients are average marginal effects of megatrend variables, for each demographic group. Robust standard errors in parentheses (clustered at the NUTS-2 level). Unweighted estimates are based on the selection model from columns (1) and (2) of Table 6, augmented with interactions between megatrends and demographic characteristics as in Eq. (2). All models include megatrends, individual characteristics, country-level controls, region (NUTS-2) FE, and year FE. Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). All models are estimated using Roodman's (2011) `cmp` STATA command, following Van de Ven and Van Praag (1981) probit sample selection model, analogous to Heckman's (1979) method. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

5.3. Additional results and checks

As briefly discussed in Section 3.3, we further explore additional aspects of unemployment, long-term unemployment, inactivity and their relationship with megatrends. While these analyses are discussed at length in the Appendix, here we briefly discuss the main results. Table B.1 reports results for the additional analyses on unemployment and long-term unemployment, while Table B.2 investigates the relationship between megatrends and inactivity, as well as the robustness of our main results.

Results for the inactivity models are reported in columns (1) to (3) and (7) to (9) of Table B.2, presenting average marginal effects of megatrends from unweighted and weighted regressions, respectively. Pooling results from models (1) and (7), inactive individuals are found to be significantly (at the 5% level) affected by digitalisation, as measured by the adoption of automation technologies. On average, a 10% increase in the stock of advanced manufacturing technology imports brings between 0.27 and 1 p.p. increase in the probability of becoming inactive. When accounting for the potential selection process behind self-reporting as deliberately inactive but still willing to work (columns (2), (3), (8) and (9)), we find that automation adoption further exacerbate exclusion risk for those individuals showing a desire to escape the exclusion trap. Specifically, once accounting for this potential heterogeneity, we find automation to significantly increase inactivity chances, on average, by between 0.22 and 0.27 p.p. following a 10% increase in digital technology adoption, while the same effect for inactive individuals expressing willingness to work spikes at between 0.77 and 0.79 p.p., as compared to those who are not.

Finally, 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 unemployment condition. To address this potential concern and provide robustness to our main results, in columns (4) to (6) and (10) to (12) of Table B.2, we report (unweighted and weighted) estimates from a three-stage sample selection model. The estimated average marginal effects from the first stage are coherent with those reported in the inactivity models: coefficients are similar in magnitude and statistical significance, while coefficient's signs are opposite as those found in the previous columns. Similarly, estimates form the second and third stages are qualitatively and statistically in line with our results from Table 9, overall supporting the robustness of our main findings.

6. Discussion, conclusions and policy considerations

This work examined the relationship between the probability of individuals to fall in labour market exclusion, as measured primarily by long-term unemployment and inactivity, and various measures of four aggregate megatrends (i.e., digitalisation, globalisation, climate, and demographic changes). Our analysis covers EU27 countries and the UK between 2009 and 2019. In exploring such relationship, we pay particular attention to the heterogeneous composition of individuals in prolonged unemployment condition over demographic groups (i.e., across gender, age groups, and educational attainment), and on how such heterogeneity moderates the relationship between megatrends and long-term unemployment.

The descriptive analysis explores in detail the composition and the evolution of unemployment outcomes and that of the various measures we use to capture each megatrend, pointing at a persistently higher labour market exclusion among middle-aged and older individuals, as well as among less educated ones. As concerns the role of megatrends, measures of digitalisation (i.e., automation adoption and innovation) hint at a growing trend over the decade-long period leading to the Covid-19 pandemic, likely to have continued during and after such economic shock. Conversely, measures proxying other megatrends like globalisation and demographic changes featured either a stable trend (e.g., GVC participation, aging, fertility rates) or a more hectic behaviour (e.g., FDI openness) over time.

Our econometric approach is based on several individual-level probit model accounting for a variety of individual-level characteristics, country-level factors, and various fixed effects, as well as for the role of potential sample selection mechanisms. We further explore empirically how demographic characteristics moderate the relationship between megatrends and protracted unemployment outcomes, uncovering that null or not significant average relationships hide significant compositional effects for some demographic groups.

The study makes a valuable contribution to the literature in two main ways. First, we provide an in-depth descriptive analysis of unemployment trends, their duration, and demographic composition across European countries. We further explore different dimensions delineating each megatrends encompassing (i) adoption and innovation trends in several digital and automation technologies, (ii) GVC participation, trade and FDI openness, (iii) extreme climate events related to both land and people, CO_2 emissions and pollutant-related mortality, and (iv) demographic changes pertaining cross-country differences in population aging, fertility rates, life expectancy and migration. Second, we contribute to the literature on labour market exclusion by providing an in-depth empirical exploration at the individual level on how all these megatrends simultaneously affect the probability of long-term unemployment, and on how demographic characteristics moderates such relationships.

Once accounting for all megatrends, as well as for potential sample selection, we uncover that most megatrends do not exert any direct effect on the average probability of individual's labour market exclusion. Notwithstanding, we find evidence that digitalisation plays a role in driving labour market exclusion outcomes. Specifically, while automation-related innovations lead to an increase in the probability of long-term unemployment, the adoption of these technologies associates with a raise in the odds of becoming inactivity. Overall, a 10% increase in patenting on automation technologies brings between 0.12 and 0.24 p.p. raise in the probability of a protracted unemployment outcome, mostly concentrated amongst males, older, and less educated individuals. Similarly, a 10% increase in the import stock of advanced manufacturing technologies imply between 0.22 and 0.79 p.p. increase in the probability of falling into inactivity. These results are coherent with prior evidence on the effect of automation technologies on unemployed workers (e.g., Olsson and Tåg, 2017; Beer et al., 2019; Blien et al., 2021; Goos et al., 2021; Schmidpeter and Winter-Ebmer, 2021) and with the polarisation mechanisms characterising automation and other digital technologies highlighted by several contributions (e.g., Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Dauth et al., 2021; Mann and Püttmann, 2023). Notably, we uncover that different aspects of the digitalisation trend (i.e., adoption and innovation) exert distinct effects of specific exclusion outcomes. Finally, although the effect of other megatrends does not necessarily appear on average, they may still affect specific categories of individuals, as highlighted by the results of our heterogeneity analysis. Our analysis reveals that trade openness provides less employment opportunities for male workers, while extreme climate events significantly relate to lower chances of labour market exclusion for males. Instead, female's long-term unemployment is negatively associated with FDI openness and fertility. Furthermore, our result reveal that education is crucial to make the most of the opportunities created by the digitalisation, globalisation, and demographic changes. Most notably, the adoption of automation technologies is bound to reduce labour market exclusion the higher the education level of individuals, which are more likely to capable to master these advanced technologies, while it may lead to a crowding-out effect for the least educated individuals. Similarly, we support the view that automation innovations can exacerbate labour market exclusion of the least educated but may create more opportunities for the highly educated.

These findings lead directly to an economic and policy debate on how to address long-term unemployment in Europe. First, and foremost, on the whole, digitalisation, globalisation, climate change and demographic change have a limited effect on long-term unemployment probability. This could reflect the fact that labour market exclusion is more likely to be affected by individual characteristics, or by other characteristics of the labour market, not captured by the regional fixed effects and which were not the focus of this study. Also, this could reflect the fact that megatrends have long-term effects, which cannot be easily gauged with the data used here. Notwithstanding, policy action around some of the megatrends may have some important effects on weaker strata of the population. For example, industrial policy aimed at sustaining the development and the adoption of advanced automation technologies and trade policies geared toward more trade liberalisation and fostering a country's connection with GVCs may offer opportunities for reducing labour market exclusion for some categories but may crowd out the least educated workers. This would suggest that such policies should be accompanied by strong interventions to increase educational attainment and capacity building.

7. References

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8. Appendix A – Additional Descriptive Statistics

Table A.1. Megatrends - digitalisation: import, export, production, and adoption of advanced manufacturing technologies (AMT) across EU27 + UK by year

	Stock of AMT imports		Stock of AMT exports		Stock of AMT production		Stock of AMT adoption	
Year	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	13.76	0.83	13.09	1.51	12.74	1.12	13.24	0.95
2010	13.87	0.80	13.20	1.44	12.87	1.01	13.38	0.85
2011	13.93	0.79	13.33	1.41	13.02	0.99	13.61	0.53
2012	14.03	0.75	13.56	1.35	13.25	0.91	13.68	0.45
2013	14.06	0.75	13.62	1.33	13.38	0.83	13.72	0.43
2014	14.09	0.75	13.70	1.30	13.45	0.79	13.73	0.41
2015	14.14	0.74	13.77	1.26	13.52	0.75	13.77	0.39
2016	14.20	0.74	13.86	1.25	13.58	0.72	13.80	0.36
2017	14.25	0.73	13.94	1.24	13.62	0.70	13.85	0.36
2018	14.30	0.74	13.99	1.23	13.66	0.69	13.89	0.38
2019	14.35	0.74	14.05	1.22	13.70	0.67	13.93	0.39
Total	14.08	0.78	13.63	1.37	13.35	0.90	13.69	0.57

Notes: Authors' own computations based on Comext, Prodcom and Eurostat data, following Castellani et al. (2022). All variables are normalised 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. Production and net consumption are computed only for technology-producing countries.

Table A.2. Megatrends - digitalisation: import, export, production and adoption of advanced manufacturing technologies (AMT) across EU27 + UK by country

	Stock of AMT imports		Stock of AMT exports		Stock of AMT production		Stock of AMT adoption	
Country	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AT	14.39	0.18	14.51	0.27	13.27	0.70	13.10	0.46
BE	14.73	0.14	14.41	0.16				
BG	12.65	0.32	12.05	0.60	11.67	0.28	12.46	0.08
CY	12.84	0.08	10.56	0.31				
CZ	14.58	0.41	14.30	0.41	12.38	0.05	12.09	1.14
DE	14.63	0.20	14.70	0.18	14.18	0.12	14.08	0.13
DK	14.36	0.24	13.97	0.34	13.62	0.23	14.12	0.17
EE	14.49	0.52	14.65	1.10				

ES	13.30	0.23	11.98	0.41	12.16	0.15	13.27	0.19
FI	14.37	0.21	14.29	0.09	12.62	0.20	13.74	0.12
FR	14.11	0.20	14.14	0.26	13.70	0.02	13.71	0.16
GR	12.84	0.09	11.05	0.04				
HR	12.99	0.16	12.42	0.24				
HU	14.95	0.12	14.85	0.31				
IE	14.89	0.03	15.66	0.21				
IT	13.58	0.12	13.31	0.12	13.80	0.12	13.97	0.12
LT	12.93	0.39	12.35	0.59				
LU	14.84	0.09	14.93	0.16				
LV	12.96	0.54	12.70	0.79				
MT	16.62	0.32	14.88	1.77				
NL	15.82	0.34	15.92	0.30				
PL	13.64	0.23	12.27	0.46				
PT	13.49	0.23	12.01	0.90	10.99	0.85	12.83	0.20
RO	13.19	0.40	12.03	0.67				
SE	14.93	0.11	14.86	0.11	13.16	0.38	13.99	0.04
SI	13.88	0.14	13.75	0.15				
SK	14.49	0.20	13.48	0.40				
UK	14.09	0.22	13.75	0.07	12.89	0.08	13.56	0.27
Total	14.08	0.78	13.63	1.37	13.35	0.90	13.69	0.57

Notes: Authors' own computations based on Comext, Prodcom and Eurostat data, following Castellani et al. (2022). All variables are normalised 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. Production and net consumption are computed only for technology-producing countries.

Table A.3. Megatrends - digitalisation: artificial intelligence, additive manufacturing, nanotechnologies and ICT patents across EU27 + UK by year

	AI		AM		Nanotechnologies		ICT	
Year	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2009	0.84	0.92	0.01	0.03	1.99	1.22	4.60	1.94
2010	0.93	0.91	0.02	0.12	2.14	1.35	4.66	1.94
2011	1.01	1.03	0.15	0.23	2.01	1.40	4.83	1.91
2012	1.36	1.17	0.34	0.40	2.19	1.49	5.17	2.01
2013	1.31	1.07	0.58	0.78	1.84	1.19	5.21	1.92
2014	1.48	1.07	0.94	1.05	1.69	1.32	5.33	1.91
2015	1.56	1.18	1.21	1.18	1.78	1.36	5.35	1.88
2016	1.83	1.28	1.52	1.42	2.02	1.36	5.36	1.92
2017	2.06	1.41	1.64	1.43	2.07	1.44	5.35	2.04
2018	2.21	1.56	1.79	1.54	1.90	1.49	5.41	1.98
2019	2.35	1.68	1.51	1.36	1.25	1.10	4.90	1.90
Total	1.51	1.31	0.85	1.20	1.91	1.37	5.10	1.96

Notes: Authors' own computations based on OECD REGPAT data. All variables are expressed in log. Patent applications to EPO, priority date, fractional count, inventor country of residence.

Table A.4. Megatrends - digitalisation: artificial intelligence, additive manufacturing, nanotechnologies and ICT patents across EU27 + UK by country

	AI		AM		Nanotechnologies		ICT	
Country	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AT	1.39	0.52	0.77	0.80	1.59	0.36	5.27	0.17
BE	1.74	0.74	0.70	0.66	2.53	0.50	5.75	0.18
BG	0.00	0.00	0.07	0.16	0.18	0.30	1.66	0.58
CY	0.00	0.00	0.00	0.00	0.08	0.20	0.87	0.60
CZ	0.10	0.26	0.10	0.23	1.09	0.51	3.03	0.28
DE	3.65	0.59	3.40	1.23	3.67	0.42	7.95	0.12
DK	0.37	0.40	0.35	0.48	1.38	0.63	5.22	0.16
EE	0.19	0.36	0.02	0.06	0.10	0.23	2.29	0.30
ES	1.92	0.50	1.29	1.24	2.81	0.30	5.32	0.13
FI	1.21	0.82	0.36	0.47	2.02	0.70	6.22	0.21
FR	3.17	0.44	1.48	1.07	3.96	0.58	7.53	0.18
GR	0.29	0.44	0.00	0.01	0.39	0.34	2.86	0.27
HR	0.06	0.19	0.00	0.00	0.11	0.26	1.20	0.47
HU	0.51	0.37	0.18	0.29	0.78	0.60	3.98	0.29
IE	1.28	0.88	0.15	0.30	1.16	0.56	4.76	0.24
IT	1.85	0.62	1.02	0.80	2.70	0.37	5.85	0.17
LT	0.00	0.00	0.02	0.06	0.20	0.32	1.30	0.58
LU	0.36	0.34	0.09	0.16	0.21	0.33	2.35	0.55
LV	0.00	0.00	0.00	0.00	0.12	0.27	1.10	0.74
MT	0.00	0.00	0.00	0.01	0.11	0.22	0.84	0.70
NL	2.27	0.97	1.18	1.17	2.97	0.65	6.48	0.16
PL	0.84	0.78	0.27	0.41	1.39	0.56	4.45	0.31
PT	0.09	0.23	0.11	0.16	0.79	0.47	3.08	0.36
RO	0.61	0.75	0.02	0.06	0.26	0.34	3.13	0.45
SE	2.23	0.57	1.05	0.70	2.43	0.64	7.07	0.21
SI	0.06	0.20	0.05	0.17	0.44	0.52	2.13	0.38
SK	0.00	0.00	0.01	0.02	0.07	0.20	2.22	0.24
UK	3.38	0.86	1.52	1.04	3.59	0.79	7.14	0.20
Total	1.51	1.31	0.85	1.20	1.91	1.37	5.10	1.96

Notes: Authors' own computations based on OECD REGPAT data. All variables are expressed in log. Patent applications to EPO, priority date, fractional count, inventor country of residence.

Table A.5. Megatrends - globalisation: total GVC participation, trade openness, FDI openness across EU27 + UK by year

	Total GVC part.		Trade Openness		FDI Openness	
Year	Mean	SD	Mean	SD	Mean	SD
2009	45.62	7.71	87.51	44.62	11.37	48.85
2010	50.05	7.30	94.68	46.70	6.93	29.98
2011	51.49	6.96	98.54	48.08	12.24	34.32
2012	51.29	6.77	99.69	47.12	11.81	57.36
2013	50.55	6.96	98.82	45.78	8.35	28.70
2014	50.37	6.95	100.02	46.52	11.60	50.96
2015	50.23	6.96	100.47	47.83	14.16	48.02
2016	49.43	7.36	100.90	51.26	14.12	28.22
2017	50.61	6.86	102.18	49.21	5.88	16.02
2018	50.86	6.72	103.83	48.43	-2.53	25.18
2019	50.55	7.07	105.39	53.74	15.97	65.62
Total	50.09	7.23	99.11	48.28	10.03	42.24

Notes: Authors' own computations based on OECD TiVA and World Bank data. Total GVC participation measured as (Backward part. + Forward part.); trade openness measured as (Exports + Imports)/GDP; FDI openness measured as (Inward FDI + Outward FDI)/GDP.

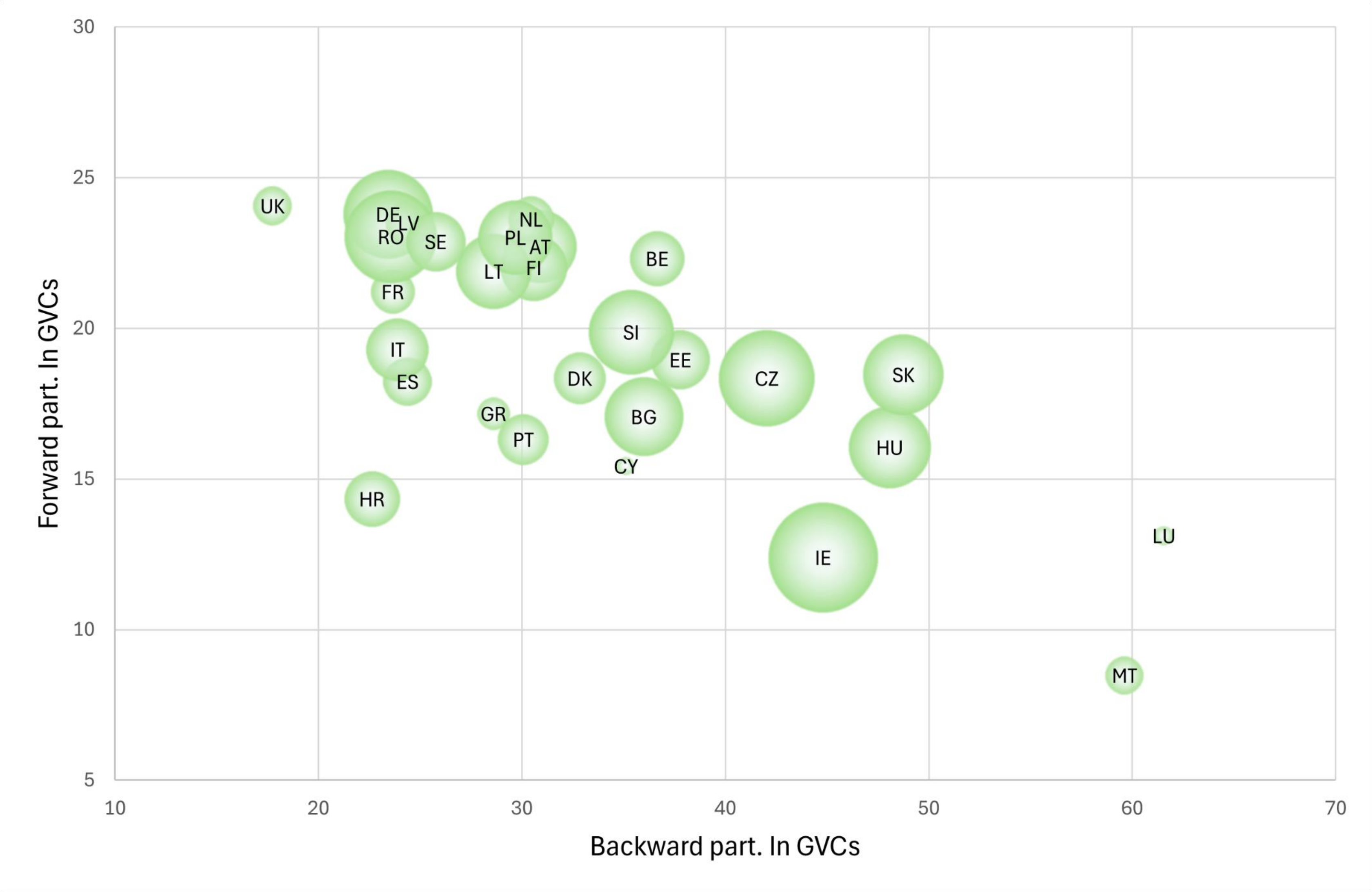
Table A.6. Megatrends - globalisation: total GVC participation, trade openness, FDI openness across EU27 + UK by country

	Total GVC part.		Trade Openness		FDI Openness	
Country	Mean	SD	Mean	SD	Mean	SD
AT	53.60	3.04	102.47	5.60	-0.50	8.45
BE	58.96	2.19	155.91	8.46	13.27	21.74
BG	53.05	2.48	120.50	11.99	4.66	1.23
CY	50.54	4.25	127.77	17.08	303.78	183.74
CZ	60.31	3.50	132.22	15.40	5.77	1.80
DE	47.21	0.86	86.18	2.28	5.74	1.68
DK	51.19	1.20	101.54	5.33	2.24	4.65
EE	56.74	2.40	151.61	13.87	8.51	7.19
ES	42.61	1.98	61.11	6.08	5.12	1.98
FI	52.59	2.08	75.34	3.29	3.96	6.45
FR	44.86	2.05	59.86	3.81	3.91	1.50
GR	45.73	2.92	63.40	10.18	1.44	0.68
HR	36.96	1.65	85.40	10.37	2.99	3.38
HU	64.12	1.75	162.25	6.72	8.26	50.99
IE	57.20	1.95	201.60	20.72	44.16	42.06
IT	43.18	2.16	55.12	3.99	2.10	1.05
LT	50.47	3.03	140.99	14.18	3.87	2.40
LU	74.59	2.85	334.59	33.13	85.97	162.68

LV	47.95	2.32	117.45	13.05	3.34	2.27
MT	68.08	2.34	303.55	9.75	-16.15	61.60
NL	54.05	2.79	146.19	12.54	41.87	43.99
PL	52.67	1.48	91.67	7.68	3.84	1.97
PT	46.38	1.87	77.43	7.40	5.92	3.50
RO	46.58	2.38	79.35	8.29	2.63	0.88
SE	48.64	1.21	84.24	2.54	4.81	3.35
SI	55.26	2.61	143.12	13.60	2.40	2.18
SK	67.20	2.64	173.24	15.96	3.95	2.88
UK	41.78	1.61	60.84	3.04	2.90	4.78
Total	50.09	7.23	99.11	48.28	10.03	42.24

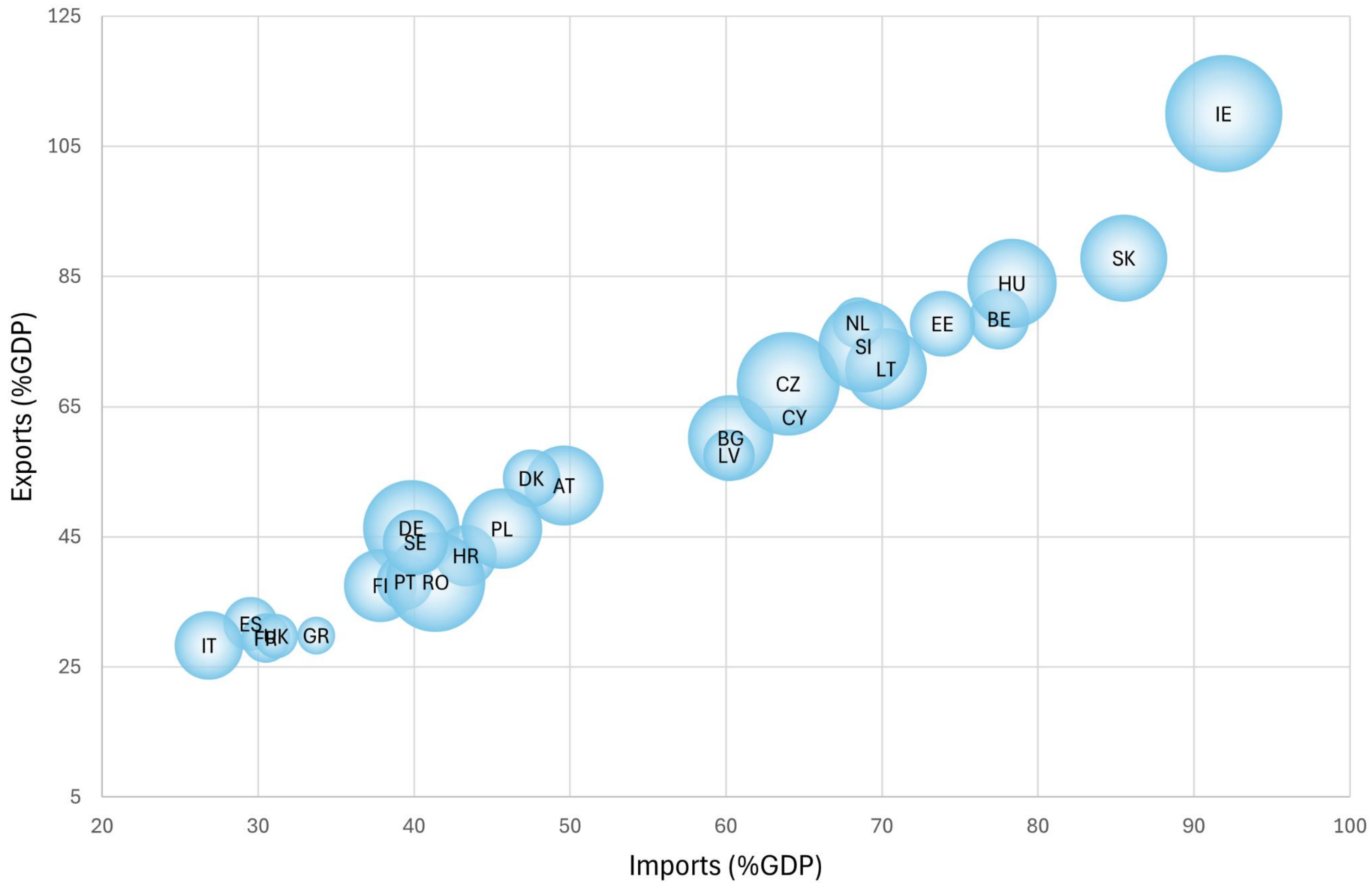
Notes: Authors' own computations based on OECD TiVA and World Bank data. Total GVC participation measured as (Backward part. + Forward part.); trade openness measured as (Exports + Imports)/GDP; FDI openness measured as (Inward FDI + Outward FDI)/GDP.

Figure A.1. Megatrends – globalisation: global value chain participation across EU27 + UK by country



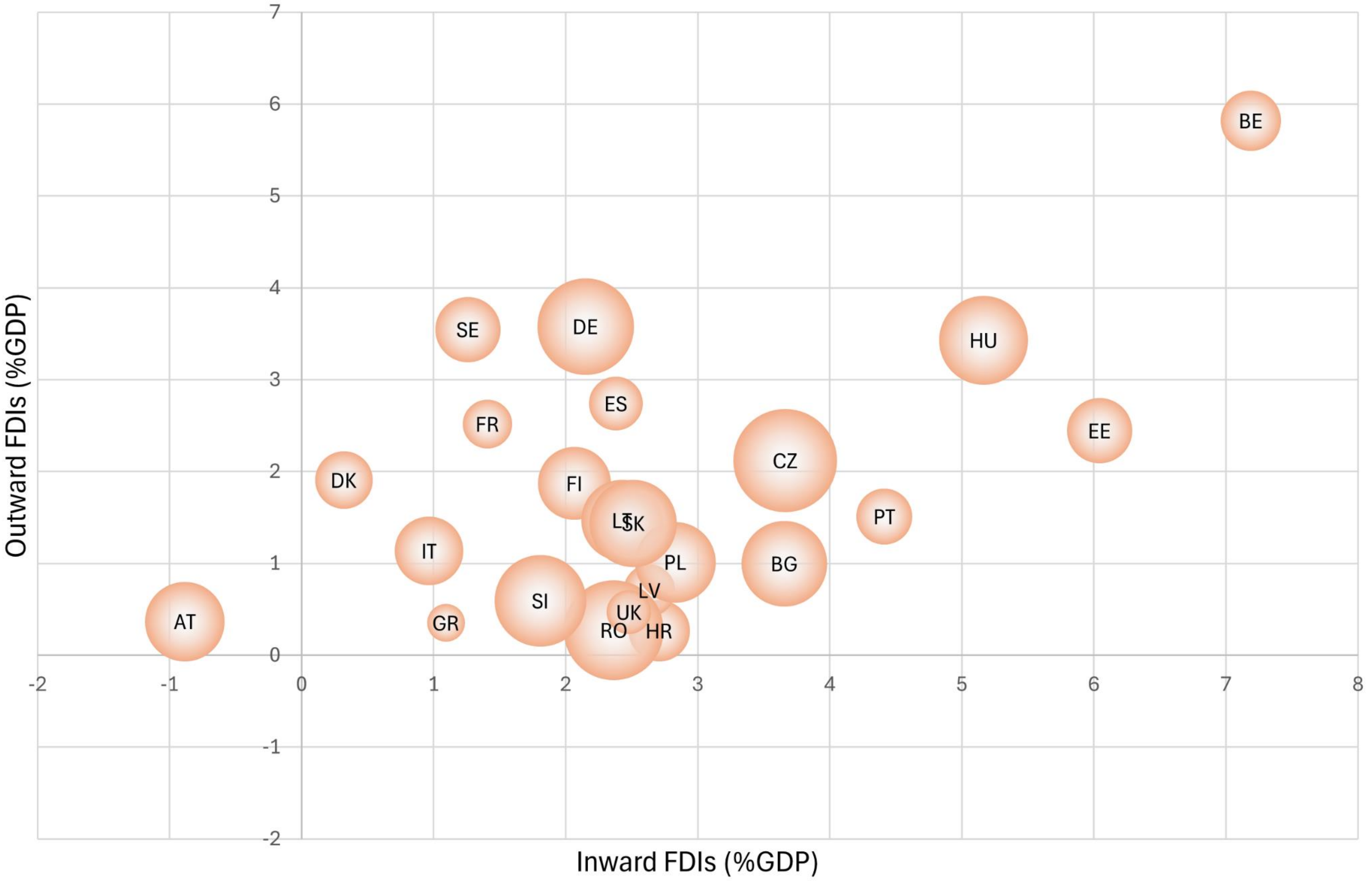
Notes: Authors' own computations based on OECD's TiVA data. Backward participation measured as foreign value-added share of gross exports; forward participation measured as domestic value added in foreign exports as a share of gross exports. Bubble size is the manufacturing share of a country's GDP. Data presented are 2009-2019 averages.

Figure A.2. Megatrends – globalisation: trade of goods and services across EU27 + UK by country



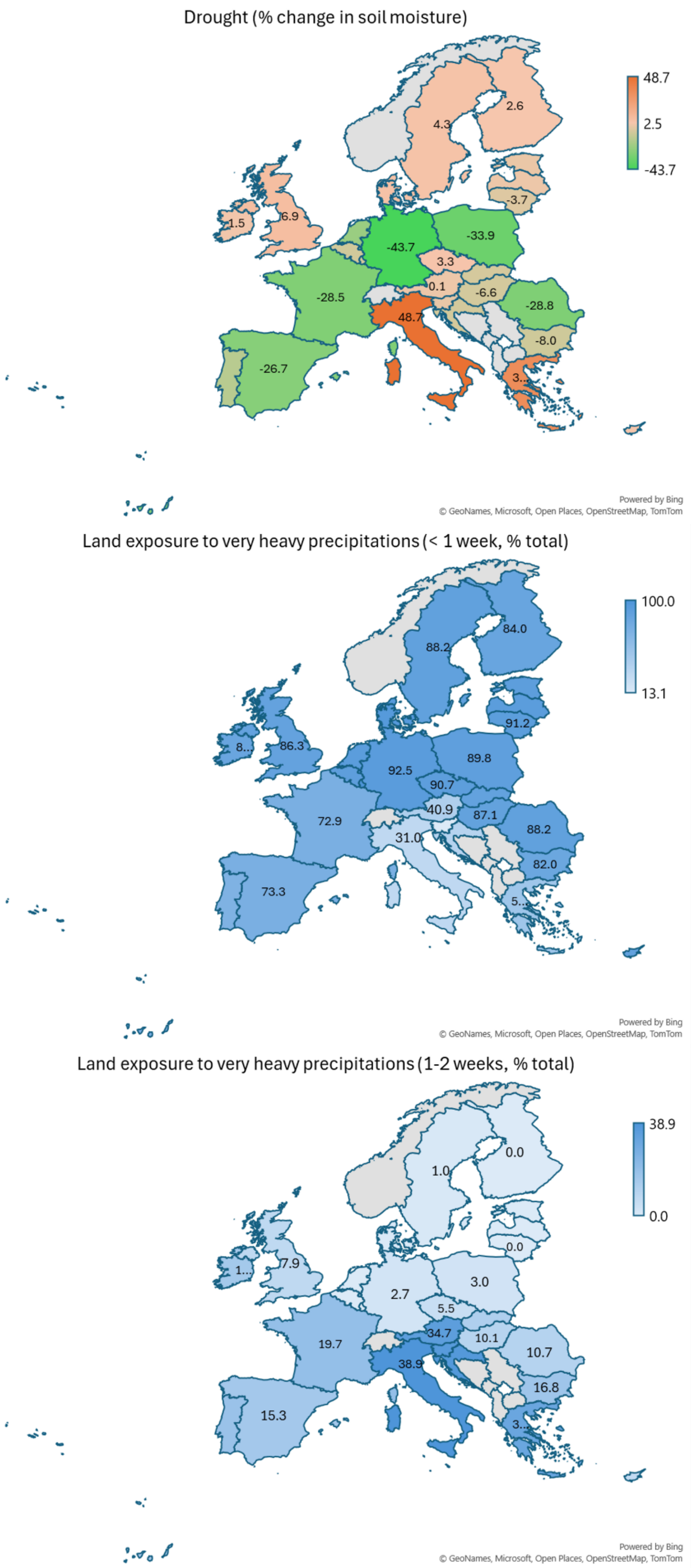
Notes: Authors' own computations based on World Bank data. Bubble size is the manufacturing share of a country's GDP. Data presented are 2009-2019 averages for selected countries; Luxembourg and Malta are excluded due to representation reasons.

Figure A.3. Megatrends – globalisation: foreign direct investment flows across EU27 + UK by country



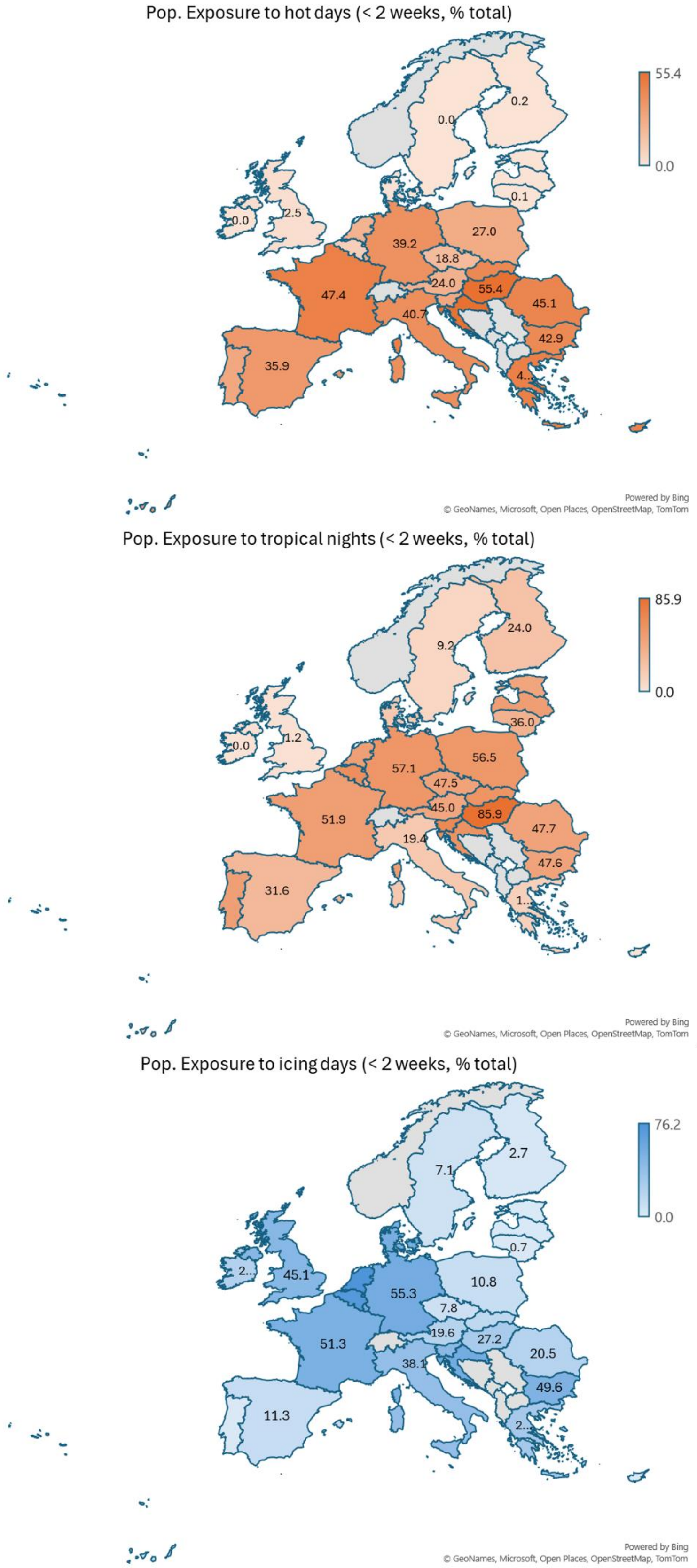
Notes: Authors' own computations based on World Bank data. Bubble size is the manufacturing share of a country's GDP. Data presented are 2009-2019 averages for selected countries; Cyprus, Ireland, Luxembourg, Malta and the Netherlands are excluded due to representation reasons.

Figure A.4. Megatrends – climate change: extreme drought/precipitation events across EU27 + UK by country



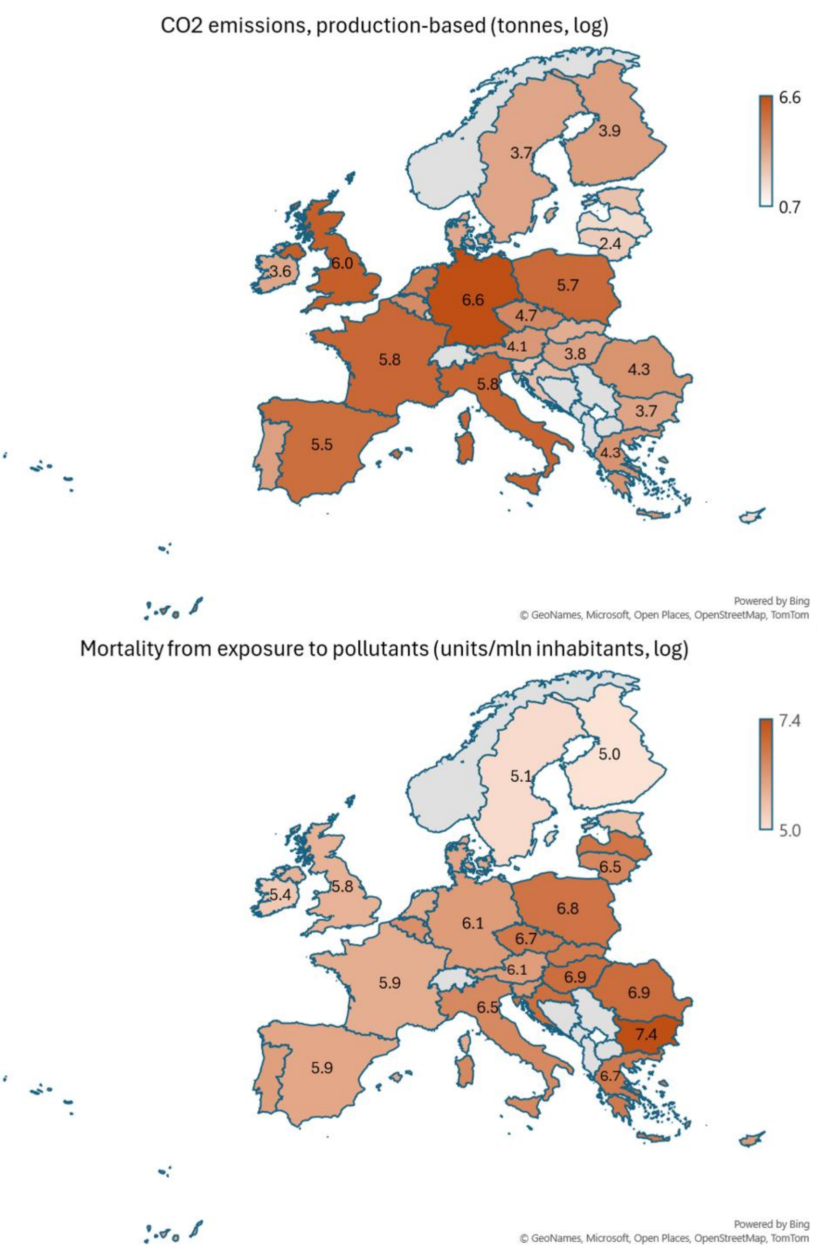
Notes: Authors' own computations based on OECD regional data on climate hazards. Data presented are 2009-2019 averages.

Figure A.5. Megatrends – climate change: extreme heat/cold waves across EU27 + UK by country



Notes: Authors' own computations based on OECD regional data on climate hazards. Data presented are 2009-2019 averages.

Figure A.6. Megatrends – climate change: CO_2 emissions and pollutant-related mortality across EU27 + UK by country



Notes: Authors' own computations based on OECD regional data on climate hazards. Data presented are 2009-2019 averages.

Table A.7. Megatrends - demographic change: population shares by age group, fertility rate, life expectancy and migration trends across EU27 + UK by country

Country	Pop. share < 14 years		Pop. share 15-64 years		Pop. share > 65 years		Fertility rate		Life expectancy		Net migration 2009-2011 (% total)		Net migration 2017-2019 (% total)	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
AT	12.28	0.23	72.31	0.17	15.41	0.33	0.38	0.03	4.40	0.01	0.28	0.07	0.46	0.05
BE	14.38	0.07	70.47	0.34	15.15	0.41	0.56	0.05	4.39	0.01	0.50	0.00	0.49	0.01
BG	11.66	0.09	71.67	0.87	16.68	0.87	0.44	0.03	4.31	0.01	-0.12	0.02	-0.18	0.01
CY	14.60	0.50	74.39	0.32	11.00	0.71	0.31	0.04	4.39	0.01	1.24	0.37	0.57	0.01
CZ	12.63	0.28	73.29	1.40	14.08	1.12	0.43	0.05	4.36	0.01	0.30	0.05	0.03	0.01
DE	11.05	0.11	71.57	0.35	17.38	0.29	0.41	0.05	4.39	0.01	0.33	0.03	0.48	0.04
DK	14.59	0.65	70.05	0.20	15.36	0.84	0.56	0.03	4.39	0.01	0.31	0.02	0.40	0.00
EE	13.38	0.28	70.92	0.89	15.71	0.62	0.48	0.04	4.35	0.01	-0.24	0.07	0.45	0.07
ES	12.72	0.18	71.94	0.55	15.34	0.67	0.28	0.03	4.41	0.01	0.18	0.07	0.69	0.25
FI	13.71	0.36	70.07	0.84	16.22	1.19	0.51	0.11	4.39	0.01	0.28	0.02	0.25	0.03
FR	15.30	0.33	69.01	0.60	15.69	0.91	0.66	0.03	4.41	0.01	0.13	0.03	0.02	0.00
GR	12.06	0.17	71.01	0.50	16.92	0.65	0.30	0.05	4.39	0.00	-0.23	0.01	-0.22	0.01
HR	12.37	0.46	71.62	0.35	16.01	0.76	0.39	0.04	4.35	0.01	-0.13	0.04	-0.32	0.01
HU	12.37	0.18	72.62	0.59	15.01	0.74	0.33	0.08	4.32	0.01	0.11	0.08	0.28	0.07
IE	18.82	0.36	70.08	0.66	11.10	0.80	0.66	0.06	4.40	0.01	-0.52	0.09	0.63	0.04
IT	11.32	0.36	70.94	0.29	17.74	0.63	0.32	0.05	4.41	0.01	0.42	0.06	0.09	0.04
LT	12.41	0.17	71.68	0.48	15.91	0.56	0.47	0.04	4.31	0.01	-0.91	0.05	-0.51	0.03
LU	14.64	0.56	72.97	0.43	12.39	0.15	0.38	0.06	4.40	0.01	1.67	0.31	1.65	0.03
LV	12.27	0.29	71.50	0.79	16.23	0.50	0.43	0.09	4.30	0.01	-0.68	0.02	-0.45	0.03
MT	11.94	0.62	73.01	0.21	15.05	0.81	0.30	0.06	4.41	0.01	0.75	0.29	2.29	0.04
NL	14.35	0.70	70.97	0.32	14.69	1.01	0.53	0.04	4.40	0.01	0.21	0.03	0.35	0.00
PL	13.14	0.20	73.82	0.91	13.04	1.08	0.32	0.04	4.35	0.01	-0.01	0.03	-0.01	0.01

PT	12.06	0.59	71.21	0.26	16.73	0.84	0.29	0.05	4.39	0.01	-0.06	0.16	0.19	0.16
RO	13.57	0.09	72.16	0.61	14.27	0.68	0.48	0.07	4.32	0.01	-0.47	0.17	-0.24	0.08
SE	14.36	0.26	69.60	0.70	16.04	0.45	0.63	0.04	4.41	0.01	0.65	0.04	0.80	0.00
SI	12.48	0.19	72.58	1.03	14.94	0.85	0.46	0.02	4.39	0.01	0.26	0.17	0.36	0.00
SK	13.58	0.13	74.25	0.91	12.18	0.98	0.36	0.05	4.34	0.01	-0.01	0.03	0.07	0.00
UK	15.10	0.05	70.10	0.55	14.80	0.58	0.60	0.05	4.39	0.01	0.45	0.01	0.35	0.01
Total	13.17	1.87	71.34	1.50	15.49	1.95	0.44	0.14	4.38	0.03	0.13	0.40	0.25	0.37

Notes: Authors' own computations based on OECD and Eurostat's country and regional statistics. Fertility is measured as number of children per woman; net migration is computed as inflows - outflows.

9. Appendix B – Additional Analyses

As discussed in Section 3.3, we also estimate additional specifications aimed at exploring further aspects of the relationship between megatrends and employment, unemployment, and inactivity outcomes, as well as to test the robustness of the main results from the sample selection model presented in the main text. To this aim, as a first step, we estimate a baseline probit regression model explaining changes in the probability of individuals becoming long-term unemployed because of the effect of aggregate megatrends. We estimate the following reduced form equation:

$$P\left(LT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \quad \text{(B1)}$$

where all variables are as described in Table 1 and Section 3 in the main text. Here, we compare individual and country characteristics of people experiencing long-term unemployment against those of all other active individuals (i.e., either employed or experiencing short-term and mid-term unemployment).

Subsequently, we narrow down our results by estimating a multivariate probit model where we jointly estimate two reduced form equations as in Eq. (1) in the main text, yet still comparing long-term unemployed individuals to all other individuals in the active population. In this way, we can ascertain the potential effect exerted by aggregate megatrends on the probability of individuals being long-term unemployed that does not depend on being unemployed *per se*, irrespectively of the duration. Finally, we estimate a standard probit model comparing long-term unemployed individuals to those in short-term and mid-term unemployment, essentially corresponding to the second stage of the sample selection model in Eq. (1).

Results for both unweighted and weighted regressions are reported hereafter in Table B.1. Overall, our estimates highlight the selection mechanism outlined in Section 3.3 to be crucial to properly measure the true effect of megatrends on changes in the probability of being long-term unemployed. Columns (1) to (5) show our estimates of Eq. (B1), where we compute changes in the probability long-term unemployment having all active individuals as baseline category. Through columns (1)-(4) we consider each set of variables related with a megatrend separately. We uncover that, on average, various aspects of digitalisation tend to exert opposite, significant effects on the probability of long-term unemployment (column (1)). While technology adoption seems to reduce labour market exclusion, innovation activity is found to increase it. Looking at globalisation (column (2)), we find no effect from neither GVC participation nor trade openness, while FDIs play a significant yet extremely small negative effect on the probability of long-term unemployment. We further observe comparable results (i.e., small in magnitude and not significant) also in the case of extreme climate event variables (column (3)), while CO_2 emissions negatively affect our outcome variable. Lastly, all demographic variables from elder population share to net migration rates play a negative short-run role in affecting long-term unemployment probabilities (column (4)), although with different magnitudes and levels of statistical significance. Then, in columns (5) and (9) – the latter, accommodating sampling weights in the estimated average marginal effects – we estimate the simultaneous effect of all megatrend variables. Considering all megatrends should exclude chances of one megatrend capturing the effect of another megatrend on long-term unemployment (e.g., population aging channelling part of the effect of rising automation, as discussed in Section 3.3). These models yield largely not significant average marginal effects, exception made for some of the variables capturing demographic trends. However, as observed from the results of the multivariate probit models, in columns (6), (7), (10), and (11), demographic changes affect all unemployed individuals (almost) evenly. At the same time, a slightly negative effect of adopting automation technologies emerges in both the jointly estimated models. Finally, the models looking solely at unemployed individuals, in columns (8) and (12), partially yield the results we observe in the main estimates in Table 9, highlighting comparable effects coming from automation innovations and trade openness, although estimated with less precision due to the neglected sample selection process.

Table B.1. Additional results: probit models of long-term unemployment and exposure to megatrends

	Unweighted estimates							
	Probit model: LT unemployed vs Active					Multivariate probit		Probit model
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Digitalisation	Globalisation	Climate change	Demographic change	All megatrends	Unemployed vs Active	LT unemployed vs Active	LT vs ST unemployed
[1] Automation adoption	-0.014***				-0.009	-0.019**	-0.010*	-0.022
	(0.005)				(0.006)	(0.009)	(0.005)	(0.026)
[2] Automation innovation	0.004***				0.000	-0.001	0.000	0.012*
	(0.001)				(0.001)	(0.002)	(0.001)	(0.006)
[3] Total GVC participation		-0.001			-0.000	-0.000	-0.000	-0.001
		(0.000)			(0.000)	(0.001)	(0.000)	(0.002)
[4] Trade openness		0.000			0.000	0.000	0.000	0.002**
		(0.000)			(0.000)	(0.000)	(0.000)	(0.001)
[5] FDI openness		-0.000***			-0.000	-0.000	-0.000	-0.000*
		(0.000)			(0.000)	(0.000)	(0.000)	(0.000)
[6] Extreme climate events 1			-0.000		-0.000	-0.000	-0.000	-0.002
			(0.000)		(0.000)	(0.001)	(0.000)	(0.002)
[7] Extreme climate events 2			0.000		-0.000	0.000	-0.000	-0.003
			(0.000)		(0.000)	(0.001)	(0.000)	(0.003)
[8] CO_2 emissions			-0.017		0.008	0.031*	0.007	-0.036
			(0.012)		(0.011)	(0.016)	(0.010)	(0.054)
[9] Pop. share > 65 years				-0.004	-0.005	-0.009**	-0.005**	-0.012
				(0.003)	(0.003)	(0.005)	(0.002)	(0.010)
[10] Fertility rate				-0.078***	-0.071***	-0.122***	-0.063***	-0.123**
				(0.011)	(0.013)	(0.022)	(0.013)	(0.057)
[11] Net migration rate				-0.007**	-0.008**	-0.020***	-0.008**	0.004

				(0.003)	(0.003)	(0.006)	(0.003)	(0.014)
Observations	2,059,993	2,059,993	2,059,993	2,059,993	2,059,993	2,059,993		184,137
Individual characteristics	YES	YES	YES	YES	YES	YES		YES
Country-level controls	YES	YES	YES	YES	YES	YES		YES
Region (NUTS-2) FE	YES	YES	YES	YES	YES	YES		YES
Year FE	YES	YES	YES	YES	YES	YES		YES
R^2	0.165	0.164	0.164	0.165	0.165	-		0.097

Notes: Reported coefficients are average marginal effects. Robust standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (1)-(8), linearized standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (9)-(12). Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). Models (6), (7), (10), and (11) are estimated using Roodman's (2011) `cmp` STATA command. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.1. (continued) Additional results: probit models of long-term unemployment and exposure to megatrends

	Weighted estimates using sampling weights			
	Probit model	Multivariate probit		Probit model
	(9)	(10)	(11)	(12)
	LT unemployed vs Active	Unemployed vs Active	LT unemployed vs Active	LT vs ST unemployed
[1] Automation adoption	-0.013	-0.029**	-0.012*	0.003
	(0.008)	(0.013)	(0.007)	(0.017)
[2] Automation innovation	0.001	-0.004	0.000	0.024***
	(0.001)	(0.003)	(0.001)	(0.009)
[3] Total GVC participation	0.000	-0.000	0.000	0.004
	(0.001)	(0.001)	(0.001)	(0.003)
[4] Trade openness	0.000	-0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.001)
[5] FDI openness	-0.000**	-0.000	-0.000**	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
[6] Extreme climate events 1	-0.000	0.000	-0.000	-0.003
	(0.000)	(0.001)	(0.000)	(0.002)
[7] Extreme climate events 2	0.000	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.004)
[8] CO_2 emissions	0.005	0.025*	0.002	-0.058
	(0.012)	(0.014)	(0.010)	(0.066)
[9] Pop. share > 65 years	-0.001	-0.002	-0.001	-0.004
	(0.004)	(0.006)	(0.003)	(0.012)
[10] Fertility rate	-0.033**	-0.071***	-0.029**	-0.010
	(0.015)	(0.025)	(0.014)	(0.089)
[11] Net migration rate	-0.008**	-0.018***	-0.008**	0.000

	(0.004)	(0.006)	(0.003)	(0.015)
Observations	2,059,993	2,059,993		184,137
Individual characteristics	YES	YES		YES
Country-level controls	YES	YES		YES
Region (NUTS-2) FE	YES	YES		YES
Year FE	YES	YES		YES
R^2	-	-		-

Notes: Reported coefficients are average marginal effects. Robust standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (1)-(8), linearized standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (9)-(12). Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). Models (6), (7), (10), and (11) are estimated using Roodman's (2011) `cmp` STATA command. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

In addition to the above discussed analyses, here we also focus on the effect that megatrends may have on inactive individuals. Within this category, we specifically focus on those individuals that in the LFS reports to be inactive and are deliberately not seeking any employment opportunity. These may be either discouraged workers (i.e., jobless people who are not searching for a job because they think no suitable job is available), truly unwilling workers, or willing workers who cannot find a job. Conversely, we exclude all those individuals that are: (i) temporarily inactive (e.g., those who, at the time of the LFS interview, reported that are going to start working in the near future); (ii) those who are studying or undergoing some form of training, and; (iii) those who are in condition of being permanently disable. First, we estimate a standard probit model comparing deliberately inactive individuals to the active population (i.e., employed and unemployed alike) following the reduced form equation:

$$P\left(INA_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \tag{B2}$$

where all variables are defined as in Table 1 and Section 3 in the main text.

Furthermore, even within deliberately inactive individuals there may be a potential selection process depending on the willingness to work they express. In fact, inactive individuals that are not willing to pursue any employment opportunity are more likely to remain locked in exclusion conditions relatively to those who are not seeking any job but nonetheless would be willing to work. To disentangle this multifaceted aspect of inactivity we estimate a sample selection model similar to that in Eq. (2) of the main text, where we compare all inactive individuals to the active population in the first stage, then in the second stage we compare inactive individuals that are willing to work to those who are not (i.e., truly unwilling workers and discouraged workers). Specifically, we estimate the following system of equations:

$$\begin{cases} P\left(INA_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(IWW_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases} \tag{B3}$$

where $INA_{i,c,r,t}$ is defined as in Eq. (B2) and in Table 1, and $IWW_{i,c,r,t}$ takes value 1 only for the subset of inactive individuals that are willing to work, 0 for those who are not.

Finally, 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 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:

$$\begin{cases} P\left(ACT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(UNE_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \\ P\left(LT_{i,c,r,t} = 1 \middle| X_{i,c,r,t}\right) = \Phi[\beta_0 + \boldsymbol{\beta}_1 \boldsymbol{MT}_{c,t} + \boldsymbol{\beta}_2 \boldsymbol{ILC}_{i,c,r,t} + \boldsymbol{\beta}_3 \boldsymbol{CLC}_{c,t} + \vartheta_r + \tau_t + \varepsilon_{i,c,r,t}] \end{cases} \quad \text{(B4)}$$

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 in the main text. This analysis essentially serves as a robustness check for our main results.

Results from the estimation of these additional models (both unweighted and weighted) are reported in Table B.2 hereafter. Models of inactivity are reported in columns (1) to (3) and (7) to (9), presenting average marginal effects of megatrends from unweighted and weighted regressions, respectively. Pooling results from models (1) and (7), inactive individuals are found to be significantly (at the 5% level) affected by digitalisation, as measured by the adoption of automation technologies. On average, a 10% increase in the stock of advanced manufacturing technology imports brings between 0.27 and 1 p.p. increase in the probability of becoming (deliberately) inactive. When accounting for the potential selection process behind self-reporting as deliberately inactive but still willing to work (columns (2), (3), (8) and (9)), we find that automation adoption further exacerbate exclusion risk for those individuals showing a desire to escape the exclusion trap. Specifically, once accounting for this potential heterogeneity, we find automation to significantly increase inactivity chances, on average, by between 0.22 and 0.27 p.p. following a 10% increase in digital technology adoption, while the same effect for inactive individuals expressing willingness to work spikes at between 0.77 and 0.79 p.p., as compared to those who are not.

Finally, in columns (4) to (6) and (10) to (12), we report results from the three-stage sample selection model in Eq. (B4). The estimated average marginal effects from the first stage are coherent with those reported in the just discussed inactivity models: coefficients are similar in magnitude and statistical significance, while coefficient's signs are opposite as those found in the previous columns. Similarly, estimates form the second and third stages are qualitatively and statistically in line with our results from Table 9, overall supporting the robustness of our main findings.

Table B.2. Additional results: probit models of inactivity, long-term unemployment and exposure to megatrends

	Unweighted estimates					
	Probit model	sample selection model, conditional mixed-process estimator		3-stage sample selection model, conditional mixed-process estimator		
	(1)	(2)	(3)	(4)	(5)	(6)
	Inactive vs Active	1st stage: Inactive vs Active	2nd stage: WW vs not WW	1st stage: Active vs Inactive	2nd stage: Unemployed vs Active	3rd stage: LT vs ST unemployed
[1] Automation adoption	0.027**	0.027**	0.079***	-0.027***	-0.021	-0.014
	(0.011)	(0.010)	(0.018)	(0.010)	(0.014)	(0.030)
[2] Automation innovation	-0.002	-0.002	-0.006	0.003	-0.003	0.012**
	(0.002)	(0.002)	(0.006)	(0.002)	(0.003)	(0.006)
[3] Total GVC participation	0.000	0.000	0.002	-0.000	-0.000	-0.001
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
[4] Trade openness	0.000	0.000	-0.000	-0.000	0.000	0.002**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
[5] FDI openness	0.000	0.000	0.000	-0.000	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
[6] Extreme climate events 1	-0.001	-0.001	-0.002	0.001	-0.001	-0.002
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
[7] Extreme climate events 2	0.000	0.000	-0.004***	-0.000	0.000	-0.003
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)
[8] CO_2 emissions	-0.017	-0.016	-0.011	0.015	0.037	-0.046
	(0.017)	(0.017)	(0.024)	(0.017)	(0.025)	(0.057)
[9] Pop. share > 65 years	0.005	0.005	-0.010	-0.005	-0.011*	-0.008
	(0.004)	(0.004)	(0.006)	(0.004)	(0.007)	(0.012)
[10] Fertility rate	-0.060***	-0.061***	0.014	0.061***	-0.189***	-0.086
	(0.019)	(0.019)	(0.044)	(0.018)	(0.033)	(0.145)

[11] Net migration rate	-0.000	-0.001	0.002	0.000	-0.027***	0.009
	(0.006)	(0.006)	(0.010)	(0.005)	(0.009)	(0.021)
Observations	2,868,663	2,868,663	808,466	2,868,663	2,059,993	184,137
Individual characteristics	YES	YES		YES		
Country-level controls	YES	YES		YES		
Region (NUTS-2) FE	YES	YES		YES		
Year FE	YES	YES		YES		
R^2	0.287	-		-		

Notes: Reported coefficients are average marginal effects. Robust standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (1)-(6), linearized standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (7)-(12). Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). Models (2)-(6) and (8)-(12) are estimated using Roodman's (2011) `cmp` STATA command, following Van de Ven and Van Praag (1981) probit sample selection model, analogous to Heckman's (1979) method. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

Table B.2. (continued) Additional results: probit models of inactivity, long-term unemployment and exposure to megatrends

	Weighted estimates using sampling weights					
	Probit model	sample selection model, conditional mixed-process estimator		3-stage sample selection model, conditional mixed-process estimator		
	(7)	(8)	(9)	(10)	(11)	(12)
	Inactive vs Active	1st stage: Inactive vs Active	2nd stage: WW vs not WW	1st stage: Active vs Inactive	2nd stage: Unemployed vs Active	3rd stage: LT vs ST unemployed
[1] Automation adoption	0.100**	0.022**	0.077***	-0.024**	-0.037*	0.021
	(0.041)	(0.009)	(0.020)	(0.009)	(0.020)	(0.025)
[2] Automation innovation	0.005	0.001	-0.004	-0.001	-0.005	0.025***
	(0.009)	(0.002)	(0.008)	(0.002)	(0.005)	(0.009)
[3] Total GVC participation	0.005	0.001	0.004*	-0.000	0.000	0.005
	(0.004)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)
[4] Trade openness	-0.000	-0.000	-0.000	0.000	-0.000	0.001
	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
[5] FDI openness	0.000	0.000	0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
[6] Extreme climate events 1	-0.002	-0.000	0.004*	0.001	0.000	-0.003
	(0.004)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)
[7] Extreme climate events 2	-0.008**	-0.002**	-0.007***	0.000**	0.000	0.001
	(0.003)	(0.001)	(0.003)	(0.000)	(0.002)	(0.005)
[8] CO_2 emissions	0.030	0.007	0.064*	-0.008	0.037	-0.074
	(0.068)	(0.016)	(0.033)	(0.016)	(0.023)	(0.054)
[9] Pop. share > 65 years	0.022	0.005	-0.004	-0.005	-0.002	-0.004
	(0.017)	(0.004)	(0.010)	(0.005)	(0.010)	(0.010)

[10] Fertility rate	-0.144	-0.032	0.012	0.036	-0.110***	0.058
	(0.093)	(0.021)	(0.050)	(0.021)	(0.040)	(0.102)
[11] Net migration rate	-0.056*	-0.013*	-0.015	0.012*	-0.030***	0.017
	(0.033)	(0.008)	(0.016)	(0.007)	(0.009)	(0.019)
Observations	2,868,663	2,868,663	808,466	2,868,663	2,059,993	184,137
Individual characteristics	YES	YES		YES		
Country-level controls	YES	YES		YES		
Region (NUTS-2) FE	YES	YES		YES		
Year FE	YES	YES		YES		
R^2	-	-		-		

Notes: Reported coefficients are average marginal effects. Robust standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (1)-(6), linearized standard errors in parentheses (clustered at the NUTS-2 level) are reported in columns (7)-(12). Individual characteristics: gender, age groups (5-years bands), education levels (ISCED), marital status, nationality, country of birth, degree of urbanisation. Country-level controls: Real GDP (log), R&D expenditure (% of GDP), agricultural sector (% GDP), manufacturing sector (% GDP), service sector (% GDP). Models (2)-(6) and (8)-(12) are estimated using Roodman's (2011) `cmp` STATA command, following Van de Ven and Van Praag (1981) probit sample selection model, analogous to Heckman's (1979) method. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

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WeLaR is Horizon Europe research project examining the impact of digitalisation, globalisation, climate change and demographic shifts on labour markets and welfare states in Europe. It aims to improve the understanding of the individual and combined effects of these trends and to develop policy proposals fostering economic growth that is distributed fairly across society and generates opportunities for all.

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