Automation and Employment over the Technology Life Cycle: Evidence from European Regions[*]

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Abstract

This paper examines the impact of digital automation technologies—ICT, robots, and software and databases—on European regional labor markets during different investment phases of technology life cycles from 1995 to 2017. We first identify major breakthroughs and phases of investment acceleration and deceleration that characterize these life cycles. We then examine how exposure to these technologies affects employment and wages during various life cycle phases. We find both positive and negative short-term effects of automation on employment within these phases, which tend to offset each other in the long run. The impact on employment rates varies by technology and phase: ICT and software have significant effects in high-productivity, service-specialized regions, while for robots, the life cycle phases are more critical than regional characteristics in explaining employment impacts.

Keywords: Automation; Technology Life Cycle; Employment; Wages; ICT; Robot
JEL Codes: J21, O33, J31

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1 Introduction

The increased codification of tasks introduces the potential for automation technologies to displace workers responsible for these tasks (Simon 1960), diminishing the demand for these jobs (Autor et al. 2003). However, the literature suggests that in the long term, short-term labor demand changes due to task codification are likely offset by enhanced productivity and economic growth (Aghion et al. 2022), increased demand for final goods (Vivarelli 1995), and the creation of new tasks (Autor et al. 2024). An underexplored question is the extent to which different vintages of digital automation technologies, each codifying different tasks, have affected labor markets in the short term and whether their impact varies across different phases of each vintage's diffusion as firms and workers adapt.

Technological advancements typically progress through incremental changes interspersed with breakthrough innovations, forming *technology life cycles* (Tushman and Anderson 1986). These cycles start with rapid developments in various configurations and applications, culminating in a dominant design (Abernathy and Utterback 1978). After standardization, the technology undergoes incremental changes followed by a decline in innovative activity, leading to the next breakthrough and subsequent life cycle. The diffusion pattern of breakthrough technology follows this cycle: after establishing the dominant design, adoption grows exponentially, then slows as it reaches and surpasses the midpoint of potential adopter saturation (Geroski 2000).

The codification of tasks and the skills required to work with new technologies change over the technology life cycle (Langlois 2003, Vona and Consoli 2015), which has two implications for research on the short-term impacts of automation on labor markets. First, the impacts may vary across different breakthrough technologies (Prytkova et al. 2024).[1] Second, the direction and intensity of labor market impacts may vary over the technology life cycle.

In this paper, we explore how short-term impacts on European regional labor markets differ across the two phases of the technology life cycles of digital automation technologies, specifically Information and Communication Technologies (ICT), Software and Database (SDB), and Robots. We identify the main breakthrough innovations within these technologies and outline their respective life cycles. We then estimate the impact of exposure to each phase on regional labor markets, distinguishing between the initial accelerated diffusion period and the subsequent decelerated diffusion period, which precedes the next technological break-

[1] Tushman and Anderson (1986) and successive work suggest that technological breakthroughs can be competence-enhancing or competence-destroying depending on which firms introduce the innovation. This affects the knowledge and skills that are replaced, reconfiguring the demand for jobs. For instance, mechanical automation, robotic automation, and intelligent robotics perform different tasks with varying abilities and connectivity within the organization, and have different implications for employment within and outside manufacturing firms (Zuboff 1988).

through.

We study the impacts on regional employment rates and average wages for a sample of 163 NUTS-2 regions in 12 European countries from 1995 to 2017. Due to the lack of firm adoption data across EU regions, we proxy the adoption life cycle at the regional level using aggregate investment information for the three technology groups. Our empirical analysis integrates data from multiple sources: EU-KLEMS (Release 2021) for ICT and SDB investments, International Federation of Robotics (IFR) data for robot investments, and ARDECO (Release 2021) for labor market outcomes.

We start by identifying technology life cycles from 1995 to 2017, based on major technological developments and investment growth in digital technologies in the EU: robots, ICT, and SDB. We identify major technological breakthroughs during this period based on changes in technology investments. Specifically, we identify three life cycles reflecting the main digital eras since the 1990s: World Wide Web 1.0 (1990–2004), Graphical User Interface and Cloud Computing (2004–2013), and Big Data and Artificial Intelligence (2013–).

We assess the impact of these automation technologies on regional labor market outcomes during the distinct technology life cycle phases. Specifically, we estimate the influence of regional exposure to these technologies on the employment-to-population ratio and average wage. To determine the effects of regional exposure to each technology, we use a shift-share instrumental variable (IV) approach, as employed in previous studies (Chiacchio et al. 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, Dauth et al. 2021). This approach is tailored to our identified technology life cycles. We use investment in these technologies during the same cycle phase in the US as an instrument to address potential endogeneity in European exposure. Categorizing regions based on their sectoral specialization and labor productivity in 1980 (i.e., before our period of analysis) allows us to investigate whether the impacts of these technologies vary with these regional characteristics. Our investigation spans the technology life cycle phases identified earlier.

The analysis yields four main results. First, we find significant short-term positive and negative impacts of ICT, SDB, and robots on the regional employment-to-population ratio during several phases of their technology life cycles. These annualized short-term effects are substantially larger than the annualized long-term effects we estimate. For ICT and SDB, this difference is due to the canceling out of short-term negative and positive effects. For robots, the difference is due to the concentration of positive impacts in the first phase of the first (1995–2001) and last life cycles (2013–).

Second, for robots, we find that the impact on employment rate and wages does not depend on regional structural differences such as sector specialization and productivity. However, for ICT and SDB, the respective positive and negative short-term impacts are mostly observed in highly productive regions specialized in services, such as densely populated urban areas.

Third, our findings suggest that the impact of ICT and SDB on the employment rate depends on the technology life cycle phase, but this is not the case for robots. Regions most exposed to ICT experience a reduction in the employment-to-population ratio during the second phase of each technology life cycle, while the first phase impact is either positive or neutral. Conversely, regions most exposed to SDB experience an increase in the employment-to-population ratio during the second phase, with either negative or no impact during the first phase.

Fourth, our results confirm that different digital automation technologies, such as ICT, SDB, and robots, have different impacts on the employment rate and average wage. In the long term, robots and ICT positively impact the employment rate, while SDB has a negative impact. However, our first result suggests that these differences are better captured by precisely identifying the technology breakthroughs, or capital vintages, likely to be adopted in the short term. Different breakthroughs have different impacts, which also depend on the phase of the technology life cycle for some of these automation technologies. This information is useful for predicting the future short-term impact of automation on employment.

This paper contributes to the extensive literature on the impact of automation technologies on labor markets (Goos et al. 2014, Chiacchio et al. 2018, Graetz and Michaels 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, Gregory et al. 2022). These studies focus predominantly on the long-term consequences of technology at various levels of analysis. US estimates indicate a negative impact of robots on employment (Acemoglu and Restrepo 2020), while findings for Europe are more mixed. For instance, Acemoglu et al. (2020) report negative employment impacts from robot investment, Dauth et al. (2021) find no significant effects, and Reljic et al. (2023) observe a positive impact. Additionally, studies differentiating among robots, CT, IT, and SDB report varying effects based on the specific technology and industry involved (Blanas 2023, Jestl 2024). Furthermore, research focusing on different periods reveals varying impacts, depending on whether substitution or compensation effects dominate. For example, Antón et al. (2022) note that the slight negative effect of robots on employment from 1995 to 2005 shifts to a positive effect from 2005 to 2015.

Our work makes two main contributions to this literature. First, we introduce a novel technology life cycle perspective for analyzing labor market adjustments in response to automation. Previous research often differentiates the effects of automation technologies based on arbitrary time periods that encompass several technological breakthroughs. Instead, we explore the short-term dynamics defined by the specific life cycle of each of the three groups of automation technologies: robots, ICT, and SDB. This approach provides a more nuanced understanding of how labor markets adjust to technological advancements within distinct phases of technology development.

We identify two different scenarios empirically. In the first scenario, during the initial phase of the technology life cycle, firms hoard technical workers as they integrate the new technology (Domini et al. 2021).[2] In the later stages of the life cycle, the technology becomes mature and standardized, firms integrate it efficiently, and task routinization is codified, leading to worker replacement.[3] In the second scenario, early adopters of breakthrough technologies, typically the most productive and advanced firms, are likely to replace workers (Autor et al. 2020). As these early adopters expand production, they potentially increase worker demand during the technology's mature stages (Vivarelli 1995). Ultimately, the prevailing scenario, and thus the impact of digital automation on employment, depends on the technology and its integration into production processes. We find that ICT follows the first scenario, SDB the second, while the impact of robots on labor markets does not depend on the technology life cycle phase.

Second, we contribute to the literature by investigating how the impacts of automation technologies on labor markets vary among regions with different initial productivity levels and sectoral specialization. For instance, Foster-McGregor et al. (2021) highlight the influence of a country's sectoral structure on its exposure to automation. Our findings suggest that regional differences are significant for ICT and SDB but not for robots.

The paper is structured as follows. Section 2 describes the variables and the databases used for our analysis. Section 3 identifies the technology life cycles and outlines the primary innovation breakthroughs for robots, ICT, and SDB. Section 4 describes the empirical methodology and our tailored IV strategy. Section 5 presents the results for the effects of automation technologies during digital technology life cycles, and discusses the principal regularities identified. Section 6 provides concluding remarks.

2 Data

2.1 Sample

We analyze the impact of technology exposure on labor market outcomes across 163 NUTS-2 regions from 12 European countries over the period 1995 to 2017. The 12 countries included

[2]This is because the routinization of tasks is incomplete and requires adjustments, necessitating technicians (Lewis 2020). Retraining existing workers is costly and time-consuming (David 1985), leading firms to reconfigure their production organization (Langlois 2003, Ciarli et al. 2021, Battisti et al. 2023).

[3]For example, Vona and Consoli (2015) note that the substitutability between workers and machines increases with technological developments as task standardization improves.

are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, and Sweden.[4]

2.2 Data Sources and Variables

Labor market. We examine labor market outcomes at the regional level, focusing on variables related to employment and wages, constructed using NUTS-2 level data from the ARDECO database (2022 release).[5]

For employment, we consider both level of employment defined as the total number of employed individuals aged between 15 and 64, and the employment-to-population ratio which is the proportion of employed people aged 15 to 64 relative to the total population.[6]

For wages, we focus on the average annual wage per worker, expressed in thousands of euros (2015 values), computed by dividing total compensation by the level of employment.

Exposure to automation technologies. We consider four automation technologies:

1. Robot: "programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning" (ISO 8373:2021);
2. Communication Technology: "specific tools, systems, computer programs, etc., used to transfer information among project stakeholders" (ISO 24765:2017);
3. Information Technology: "resources required to acquire, process, store and disseminate information" (ISO 24765:2017);

4a. Computer Software: "computer programs, procedures and possibly associated documentation and data pertaining to the operation of a computer system" (ISO 24765:2017);

4b. Database: "collection of interrelated data stored together in one or more computerized files" (ISO 24765:2017).

[4]We exclude Eastern European countries for two methodological reasons: first, data on initial sectoral employment shares in 1980 required by our shift-share design to measure the technology exposure of European regions are not available for some of these countries, and second, identification of automation technology investment cycles requires a balanced panel of technology stocks for the period 1995-–2017. Our objective is to assess the impact of exposure to automation technologies across the entire set of countries and an unbalanced panel would bias the identification of these cycles towards the subset of countries with data available up to 1995.

[5]ARDECO stands for 'Annual Regional Database of the European Commission' and is elaborated and maintained by the Directorate General for Regional and Urban Policy in the Joint Research Center. It has information on population, employment (persons and hours worked), wages, labor costs, domestic product and capital formation since 1980 at NUTS-3, NUTS-2, NUTS-1 and country level. The employment variables are disaggregated at broad sectoral levels. Table A.1 summarizes the industry classification.

[6]We acknowledge that the ratio suffers from the limitation that the nominator growths more than the denominator as result of the aging population. However, in the ARDECO database we only have information for the total population, so it is not possible to exclude people with 65 or more.

We consider computer software (4a) and database (4b) as a single technology based on the available data.

We use the number of robots (i.e. robot stock) in use in each sector at the country level from the 2019 Release of the IFR data (see Jurkat et al. (2022) for a comprehensive review). Robots are present in three out of six sectors: Industry (B-E), Construction (F), and Non-Market Services (O-U).[7] Since approximately 30% of robots are unspecified (i.e. not assigned to a particular sector), we distributed them proportionally across sectors based on sectoral share.[8] Additionally, for some countries (such as the US) where numbers of robots are not available at the sectoral level for certain years, we estimate their number by distributing the total number of robots weighted by the average sectoral share using years with available data.[9]

ICT and SDB data are from the EU-KLEMS database (Release 2021). We capitalize on the fact that this database distinguishes between these technologies which allows us to analyze the stock of communication equipment and computing equipment (i.e. ICT), and computer software and database (i.e. SDB) at the country-industry level. Our measures for these technology stocks are capital stock (in 2015 volumes), derived from national accounts.[10][11] For Denmark and Sweden, we converted EUKLEMS figures into euros using the nominal exchange rate from EUROSTAT.

Control variables. To account for other factors that might influence regional labor market outcomes, we include two control variables (both in shift-share) to isolate the role of investment in automation. First, we adjust for changes in final domestic demand using the real consumption index from the Inter-Country Input-Output database.[12] We do this to absorb

[7]It is worth noting that IFR Release 2019 has information at ISIC Rev. 3.1. As the rest of our data sources are at ISIC Rev. 4 (which corresponds to NACE Rev. 2), we harmonized them to be compatible with the latter classification. Given that we work at 1-digit level industry level and even further aggregations, constrained by the ARDECO database, this does not imply major distortions. Tables A.1 and A.2 provide more details on the harmonization.

[8]Specifically, we calculated the ratio of the number of robots in each sector to the total number of robots assigned to sectors and allocated the unspecified robots based on these ratios. While some studies do not distribute unallocated robots across sectors (see Graetz and Michaels 2018, Dauth et al. 2021), in our case, doing so ensures a harmonized series that is comparable when aggregating our measure of technology exposure across sectors.

[9]For instance, suppose that for a specific country, sectoral robot stock data are missing for 1995 to 2000. We then calculated average sectoral shares from 2001 to 2017 and imputed numbers for the earlier years by applying these estimated shares to the total robot count.

[10]Investment would have been a better measure due to small differences in accounting for depreciation across national statistical offices. However, in the case of the IFR data on robots due to the different compliance rules described in Jurkat et al. (2022) robot flows (robot installations per year) are tracked inconsistently across countries. Since inconsistent data on stocks from EUKLEMS is less problematic, we use stocks.

[11]For Ireland, technology stock data are available at the country but not the sectoral level. For this country, we estimated them by allocating country-level technology stocks to the respective sectors in Ireland based on sectoral share in Ireland's gross fixed capital formation.

[12]OECD (2021), OECD Inter-Country Input-Output Database, http://oe.cd/icio. Release: November 2019.

the effect associated to business cycles in our outcome variables. Second, we consider the potential impact of trade and international competition by controlling for imports from China recorded in the OECD Trade in Value Added database.[13] Increased trade with emerging countries has been shown to have adverse effects on manufacturing employment (Autor et al. 2013, Dauth et al. 2014, Autor et al. 2015).

Instrumental variable. To address the endogeneity in the relationship between the decision to invest in automation technologies and labor market outcomes, we use data on investment in the United States in similar automation technologies as an instrument for investment by European regions. These data are from the IFR (for robots) and EU-KLEMS (for ICT and SDB).[14] To construct our instrument (described in Section 4), we normalize the technology stock using sectoral employment data from 1980, sourced from the OECD Annual Labour Force Statistics (ALFS).[15]

3 Technological Breakthroughs and their Life Cycles

Similar to innovations in other technologies, automation innovations tend to cluster temporally around major breakthroughs, promoting a series of incremental innovations that lead to the next major advancement (Silverberg and Verspagen 2003).

In this section, we qualitatively identify the primary innovation breakthroughs in digital technologies (robots, ICT, and SDB) since 1990 by combining insights from the innovation and engineering literature. Next, we analyze the diffusion of these breakthroughs across Europe over time, examining investment trends in these technologies. We differentiate between periods of accelerated investment (early adoption of new technology) and slower investment (late adoption of mature technology) before and after each breakthrough.

3.1 Breakthroughs in Digital Technologies: From the Web 1.0 to Big Data and AI

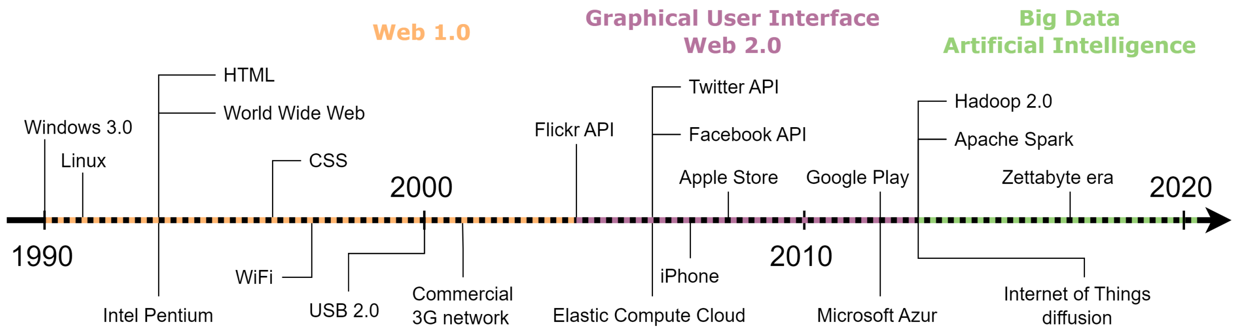
The ICT revolution, which began in the early 1970s, has been described as "a set of interrelated radical breakthroughs, forming a major constellation of interdependent technologies" (Freeman and Perez 1988, Perez 2010). Nuvolari (2020) identifies four major interdependent technological ICT elements: electronic components, computational power (semiconductors

[13] OECD (2021), OECD Trade in Value Added Database, http://oe.cd/tiva. Release: November 2021.

[14] Sectoral robot data for the U.S. are available from 2004. We impute earlier data using the methodology explained earlier in this section.

[15] OECD (2022), OECD ALFS, https://stats.oecd.org/.

Figure 1: Main Digital Technology Innovations Since 1990



Notes: Figure 1 presents the main digital technology innovations since 1990. The 3 digital technological cycles are Web 1.0 (1990 to 2004), Graphical User Interface and Web 2.0 (2004 to 2013), and Big Data and Artificial Intelligence (from 2013).

and computers), software, and networking equipment. Radical advancements in these components can lead to significant innovations in ICT. In particular, the development of microprocessors was central to the ICT revolution, enhancing the computational capacity of electronic devices such as computers while also reducing their cost (Freeman and Louçã 2001).

Figure 1 presents the main digital technology innovations since the 1990s and highlights three major radical shifts in various ICT components (breakthroughs): Web 1.0 (1993–2004), Graphical User Interfaces and Cloud Computing (2004–2013), and Big Data and Artificial Intelligence (AI) (2013–present). We highlight the main features of these three breakthroughs here and provide a more detailed description of the technologies and their components in Appendix E.

Web 1.0. During the 1990s, the reduced size and cost of microprocessors significantly increased the adoption of personal computers. The introduction of user-friendly operating systems such as Windows 3.0 and Linux led to the widespread adoption of computers (IT). Alongside these technical changes, the emergence of the World Wide Web (WWW) in 1993 facilitated the adoption of the Internet (CT) by businesses (e.g., e-commerce) and end-users. While software development, notably Windows 3.0, played a crucial role in disseminating ICT to end-users, investment in databases was limited.

Advancements in ICT and SDB laid the foundations for advances in industrial robots. The development of robotics in the 1990s built on three main technologies integral to the third generation of robots (1978–1999) identified by Gasparetto et al. 2019. These technologies include remote and self-programming capabilities enabled by microprocessors, sensors, and rudimentary 'intelligence' for diverse condition responses and environmental interactions (e.g., visual or tactile inspection and servo controls), and the capability for six-axis movements (see discussion in Savona et al. 2022). Advances in communication protocols during the 1990s, including the Internet, the WWW, and wireless technologies, further expanded control capabilities and spatial movements, leading to the emergence of mobile robots (Grau et al. 2017). This expansion impacted the automobile industry and, crucially, other manufacturing industries (Hägele et al. 2016, Gasparetto et al. 2019).

Graphical User Interface and Cloud Computing. The second technological breakthrough was marked by the emergence of Web 2.0 technologies in the early 2000s, following significant advancements in Graphical User Interface (GUI) and Cloud Computing. Previous digital infrastructure developments (i.e., the Internet and mobile communication) spurred the creation of user-friendly devices such as smartphones. This era gave birth to significant network economies (Mansell 2021) and the proliferation of new service applications (e.g., social media, electronic commerce, search engines, data analytics). During this period, databases also became increasingly central to both final and intermediate demand, as computational power grew and Application Programming Interfaces (APIs) were developed.

Regarding robots, while they improved over the years, there was no radical change in the technology, but rather a continuation of the technological patterns observed in the early 1990s. The integration and advancement of Industry 4.0 technologies in the early 2000s marked the advent of a new era in robotics.

Big Data and Artificial Intelligence. The third technological breakthrough is characterized by the latest wave of AI, driven by increased investments in neural networks and deep learning. This period is marked by advancements in machine learning and deep learning algorithms, enabled by the growing availability of large data sets (big data) and rapid increases in computational power (facilitated by cloud computing). Significant enhancements to networking and communication technologies have enabled the diffusion of the Internet of Things (IoT).[16]

The evolution of these digital technologies has enabled a significant shift in robotics. The development of AI technologies, in parallel with the emergence of the IoT and sophisticated sensors, paved the way for intelligent computing systems. More sophisticated sensors and wireless communication technologies allow complete mobility on manufacturing floors and self-coordination involving swarms of devices (IoT). These radical developments have increased the autonomy of robots, their ability to collaborate with humans, and their precision in various industrial applications (Müller 2022).

[16] The IoT can be defined as a suite of technologies that allow physical objects (equipped with sensors) to communicate and exchange data with computing systems via wired or wireless networks without human intervention (Lee 2017). Alongside social media platforms, the IoT is promoting data generation and further AI developments.

In summary, during the period analyzed (1995–2017), we identify three primary developments (breakthroughs) in digital technologies. The first breakthrough is the emergence of Web 1.0 technologies and software, alongside cheaper computing costs and rapid advances in user-friendly software (1990 onwards). The second breakthrough is the emergence of Web 2.0 and GUI, with simplified data acquisition technologies (e.g., APIs), cloud computing, and storage (2005 onwards) as the main milestones of this era. During this period, we also observe enhancements in flexibility, control, and sensing capabilities with the third generation of robots.[17] Finally, the AI and connectivity (IoT) revolutions (2013 onwards) align with the introduction of the fourth generation of intelligent robots, which built on developments in AI (2010 onwards).

3.2 Technology Life Cycles in Digital Technologies

We examine investment in digital technologies since 1990. The aim is to determine whether the pace of investment changes throughout each breakthrough's life cycle—typically accelerating adoption following a breakthrough and decelerating before the next one.

We analyze investment patterns in digital technologies (ICT and SDB) aggregated at the European level.[18] We aggregate investment stock in these technologies (per thousand workers in 1980 at constant prices) across all European countries.[19] As expected, investment in digital technologies has increased annually since 1990 (see Figure D.3 in the appendix).

To assess the rate of increase, in Figure 2, we calculate the first difference in the time series after applying a 3-year moving average to smooth short-term fluctuations. The left y-axis depicts the change in investment in digital technologies. To differentiate technology-driven investment from business cycles, we also show the trends in final demand (real household consumption) on the right y-axis as a proxy for the latter.

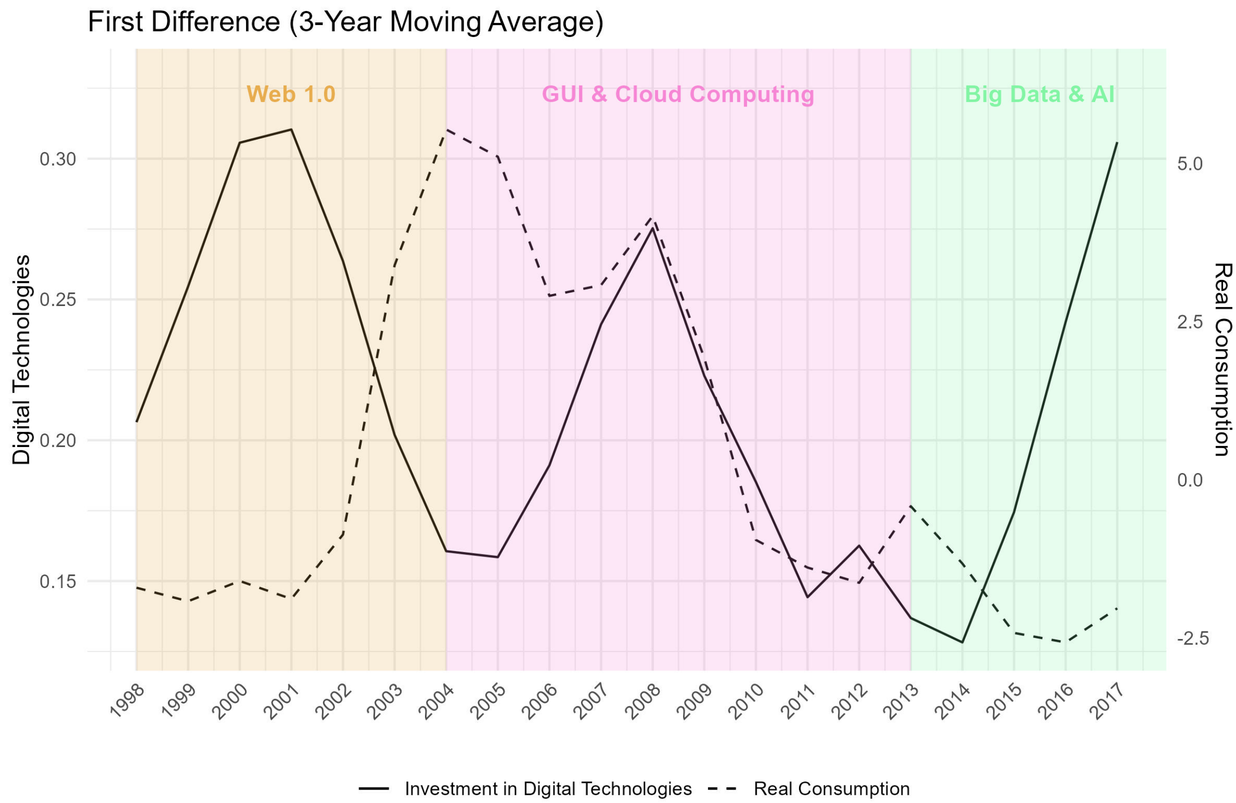
The patterns of investment in digital technologies from 1995 to 2017 show three stages of acceleration and deceleration. The Web 1.0 breakthrough in the early 1990s was followed by an investment acceleration phase that persisted until around 2001, succeeded by a declining rate of change up to around 2004/5. This period coincided with the emergence of the second

[17]To clarify, the core technologies that led to robot improvements in the early 1990s prevailed until the early 2000s.

[18]We cannot aggregate robots with ICT and SDB, as robot data is measured in units, while the former are measured in monetary value. However, analyzing changes in robot stock separately reveals significant shifts in the pace of investment that align with ICT and SDB. This can be observed in Figure D.4 in the appendix.

[19]The technology stocks are calculated in volume terms and are not directly additive. Therefore, we used the EU-KLEMS methodology to generate aggregates (EUKLEMS&INTANProd 2021). We calculated aggregation at the European level at both the current and previous year's prices and derived a European-level volume index, which we used to chain-link the values using 2015 as the base year. We then normalized the series by employment aggregated at the European level in 1980.

Figure 2: Investment in Digital Technologies and Final Demand in First Difference



Notes: This figure depicts the evolution of the first difference in digital technologies (left y-axis) and real consumption (right y-axis) per thousand workers at the EU level, aggregated for the 12 European countries in the sample. Both series are smoothed by taking the 3-year moving average. Digital technologies comprise ICT and software and databases. The data on consumption correspond to the final consumption expenditure of households from the OECD Input-Output Tables (2021 edition). This series has been adjusted into real consumption figures by deflating it with the consumer price index provided by the OECD (base year 2015=100).

breakthrough in our timeframe: GUI and cloud computing. Investment again accelerated from 2008 to 2011, depending on the technology group, and then declined before the next breakthrough (big data and AI) in 2014. The third technology cycle began in 2014, with all three technologies experiencing ongoing increases in investment up to 2017. The trends in digital technology investment substantially differ from those in real consumption, where we observed a sharp acceleration up to 2004, followed by a deceleration trend.

Although there is some overlap in the trends of both series during the second phase of the GUI & Cloud Computing era, Figure 2 shows that digital technology investment diverges from business cycles.

Table 1 summarizes the technology life cycle phases. The investment patterns in digital technologies in Europe qualitatively indicate a technology lifecycle characterized by increasing rates of adoption following each breakthrough in the various components of these technologies and decreasing rates prior to the next breakthrough. The trends in investment in digi-

Table 1: Phases of the Technology Life Cycles

Cycle	Phase	Period
Web 1.0	$\uparrow$	1995-2001
	$\downarrow$	2001-2004
GUI & Cloud Computing	$\uparrow$	2004-2009
	$\downarrow$	2009-2013
Big Data - AI	$\uparrow$	2013-2017

Notes: This table summarizes the years of each phase in the technology life cycles of digital technologies. A $\uparrow$ indicates the first phase of rapid diffusion of early vintages of the technology, whereas a $\downarrow$ indicates the last phase of slower diffusion of later vintages of the technology.

tal technologies and the discussions in Section 3.1 imply the presence of distinct phases in the evolution and use of these technologies, with potentially varying impacts on the labor market. Therefore, in what follows, the phases of acceleration and deceleration along the technology lifecycle will be the time periods in our labor market analysis.

Robustness checks. To validate our results, we also tested an alternative methodology. We regressed the investment time series for digital technologies against a linear time trend and real consumption per thousand workers in 1980 aggregated at the European level.[20] The results are depicted in Figure D.3 in the appendix. The second panel shows the residuals after regressing the time series on a linear time trend, and the third panel presents the residuals after including both the time trend and real consumption. It follows that the evolution of the first difference series, and consequently, the phases of investment, are extremely similar to those in Figure 2. Hence, we can be confident that our approach captures periods of rapid change (either increase or decrease) in technology investment.

4 Empirical Specification

Having delineated the technological breakthroughs in digital technologies, we next evaluate the impact of investment in robots, ICT, and SDB on regional labor markets in Europe. The availability of country-level data on robots, ICT, and SDB investments allows us to calculate technology exposure (i.e., change in the technology stock) as a shift-share instrument across different phases of digital technology cycles. We estimate our baseline model for labor market

[20]We controlled for final demand, real consumption per thousand workers, to account for business cycle effects in investment in these technologies.

adjustments in response to technology exposure throughout these lifecycle phases. Finally, to address identification issues, we implement an IV strategy that uses US technology investment as an instrument for technology investment in European regions.

4.1 Shift-share Technology Exposure in Technological Investment Phases

We measure exposure of a European region r to technology K between years t and $t+h$ using the standard shift-share measure in the literature (Chiacchio et al. 2018, Acemoglu and Restrepo 2020, Dauth et al. 2021). Formally,

$$(Exposure_r^K)_t^{t+h} = \sum_{i \in I} l_{ri,1980} \left(Tech_{c(r)i,t+h}^K - Tech_{c(r)i,t}^K \right), \tag{1}$$

where $l_{ri,1980}$ is the share of employment of sector i in region r in 1980, and $Tech_{c(r)i,t}^K$ is the level of technology stock $K \in \{ROB, ICT, SDB\}$ per thousand workers in sector i at the country level $c(r)$ in year t.[21]

We adjust our shift-share design to account for the segmentation of the period from 1995 to 2017 into sub-periods representing the different phases of the technology life cycles.

Consider the year $t+h'$ as a breakpoint (i.e., any intermediate year between 1995 and 2017) delineating two phases. We can divide the exposure defined in Equation (1) into the phase *before* the breakpoint and the phase *after* the breakpoint, such that:

$$\begin{aligned}(Exposure_r^K)_{1995}^{2017} = \sum_{i \in I} l_{ri,1980} \Big(& Tech_{c(r)i,2017}^K - Tech_{c(r)i,t+h'}^K \\ & + Tech_{c(r)i,t+h'}^K - Tech_{c(r)i,1995}^K \Big).\end{aligned}$$

By regrouping the terms and using the exposure definition derived from Equation (1), total exposure can be expressed as the sum of the exposures in both phases:

$$\begin{aligned}(Exposure_r^K)_{1995}^{2017} = & \underbrace{\sum_{i \in I} l_{ri,1980} \left(Tech_{c(r)i,2017}^K - Tech_{c(r)i,t+h'}^K \right)}_{\equiv Exposure_{r,2}^K} \\ & + \underbrace{\sum_{i \in I} l_{ri,1980} \left(Tech_{c(r)i,t+h'}^K - Tech_{c(r)i,1995}^K \right)}_{\equiv Exposure_{r,1}^K},\end{aligned}$$

where 1 refers to the technology investment phase between 1995 and $t+h'$ and 2 to the tech-

[21] Consequently, our change in exposure is confined to changes in the technology stock. The sectoral shares of employment in the region remain constant, and to avoid endogeneity issues, we use 1980 values.

nology investment phase between $t+h'$ and 2017. This split in exposure can be generalized to any number of phases as follows:

$$(Exposure_r^K)_{1995}^{2017} = \sum_{\tau \in \mathcal{T}} Exposure_{r,\tau}^K, \tag{2}$$

where τ is an investment phase.

Similarly, we consider labor market adjustments over the different phases of technological investment. This division is straightforward:

$$(y_r)_{1995}^{2017} = \sum_{\tau \in \mathcal{T}} y_{r,\tau},$$

which represents the change in the labor market outcome variable for region r during the phase τ.

In the remaining sections of the paper, the time units for analysis are the phases of investment acceleration and deceleration, τ, identified in Section 3.2.

4.2 Baseline Specification

To assess the relationship between labor market adjustments and exposure to technology K throughout the various phases $\tau \in \mathcal{T}$ of digital technology life cycles, we use the following specification:

$$y_{r,\tau} = \alpha + \beta_1 Exposure_{r,\tau}^{ROB} + \beta_2 Exposure_{r,\tau}^{ICT} + \beta_3 Exposure_{r,\tau}^{SDB} + X'\gamma + \phi_{c(r)} + u_r, \tag{3}$$

where $y_{r,\tau}$ represents the *annualized* change in the outcome variable for region r during phase τ,[22] $Exposure_{r,\tau}^K$ is the region's exposure to technology K during the same phase, X represents control variables (including the log of the population, the change in final demand, and trade exposure), $\phi_{c(r)}$ are country fixed effects, and u is the error term. Observations are weighted by the population in 1980.

We standardize technology exposure at the phase level to facilitate the comparison of effect magnitudes across different technological phases and enhance the interpretability of the coefficients. Thus, the β coefficients can be interpreted as the annual change in the outcome variable y for a one-standard-deviation (1-STD) change in exposure to technology K during the phase τ of the technology life cycle.

Changes in levels of employment and average wage are both calculated as log changes, al-

[22] We consider the annualized changes since cycle phases have different lengths. This facilitates comparisons across cycle phases.

lowing the coefficients to be interpreted as percentage changes. Changes in the employment-to-population ratio are computed directly, meaning that the coefficients can be interpreted as percentage point (pp.) changes.

4.3 Identification and IV strategy

The relationship between investment in automation technology and employment and wage outcomes is endogenous. First, the decision to invest in automation technologies is influenced by labor costs and availability (Bachmann et al. 2022), including labor market institutional factors (Presidente 2023). Second, some common industry-region level determinants of automation and labor, such as labor institutions and skills are not directly observable. The direction of the bias will differ for employment and wages, and will depend on the omitted variable. For instance, a pool of more skilled workers is likely to favor both adoption and employment (through productive and sales). Controlling for real consumption (as a proxy for demand shocks and the business cycle), trade exposure, and country fixed effects partially but not completely mitigates this issue. Third, measuring automation technologies presents several challenges. Not all robots included in the IFR data are allocated to sectors. Moreover, tangible and intangible capital (such as ICT and software) measurement and accounting methods differ across countries and over time, and is only partially harmonized in the EU-KLEMS data, which means that the estimates derived from Equation (3) may be downward biased. The overall direction of the OLS bias, given simultaneity, omitted variables, and measurement errors, depends on the prevailing source of endogeneity, for different technologies.

Following the prevailing IV strategy used in Acemoglu and Restrepo (2020) and Antón et al. (2022), we use technological investment data for the U.S., a large country undergoing significant automation.[23]

We construct the exposure of European regions over a period by measuring the change in automation technologies in the U.S. (exogenous shift) over the same period, maintaining the initial employment shares from European regions (share). The instrument is defined as:

$$Exposure_{r,\tau}^{K,US} = \sum_{i \in I} l_{ri,1980} \left(Tech_{i,t+h}^{K,US} - Tech_{i,t}^{K,US} \right), \tag{4}$$

where $l_{ri,1980}$ is the share of employment of sector i in European region r in 1980, and $Tech_{i,t}^{K,US}$ is the level of technology stock K per thousand workers in sector i in the U.S. for year t. The

[23]Some studies use data from other European countries (Aghion et al. 2019, Dauth et al. 2021, Bachmann et al. 2022). However, compared to employment trends between EU countries and the U.S., employment trends in EU countries are more closely correlated due in particular to global value chains and human capital flows. US investments in automation are less likely to impact European labor markets directly.

years t and $t+h$ correspond to the start and end of the cycle phase τ, respectively.

By considering changes in technology in the U.S., we capture shifts in technology that influence its diffusion in Europe, although exogenous to regional labor markets in Europe. We allocate investment proportionally according to the exposure of each region in 1980, based on its sectoral specialization.

We use the following first-stage specification for each phase τ:

$$Exposure^{K}_{r,\tau} = \alpha + \beta \times Exposure^{K,US}_{r,\tau} + \varepsilon_r, \tag{5}$$

where $Exposure^{K}_{r,\tau}$ is the baseline exposure to technology K in the European region r for the phase τ, as defined in Equation (1), $Exposure^{K,US}_{r,\tau}$ is the instrument for the phase, as outlined in Equation (4), and ε_r is the error term. Tables C.4, C.5, and C.6, in the appendix, present the first-stage regressions for robots, ICT, and software–databases, respectively.

4.4 Regional Clusters

To investigate how the effects of automation vary across types of regions with different characteristics, we categorize them based on sectoral specialization and labor productivity.

To measure sectoral specialization, we use a k-means algorithm with regional employment shares in 1980 across three broad sectors—agriculture, industry, and services—as clustering variables.[24]

Our preferred specification identifies three distinct groups: agriculture-intensive, industry-intensive, and service-intensive. Figure D.1 shows the geographical distribution of regions from our cluster analysis. Table B.1 presents the number of regions in each cluster and their within-cluster averages (centers).

Similarly, we use regional labor productivity in 1980 and classify regions as high or low productivity based on whether their productivity level is above or below the median for the entire sample of regions.[25] Figure D.2 depicts the distribution of regions by productivity level relative to the overall sample of regions.

To account for cluster type and productivity level, we interacted technology exposure K with slope dummies for cluster and productivity level. We perform separate regressions for both the cluster and productivity categories, increasing the granularity of our analysis.

[24]Sectors from NACE Rev. 2 have been grouped as follows: Industry includes major groups B to F and Services G to U.

[25]Labor productivity is calculated as the ratio of Gross Value Added (GVA) at constant prices to employment (in thousands) in 1980 for each region. For Greece and Ireland, where GVA data before 1995 are unavailable, we use 1995 data for these calculations.

5 Labor Market Impacts of Different Technology Vintages

In this section, we examine the results of our estimations of the impacts of exposure to digital automation technology on the labor market during different phases of digital technology life cycles. We first assess the differences between the effects over the long term (i.e., 1995–2017) and the short term (i.e., during each phase). We then identify patterns in how digital automation technologies have affected the employment rate in European regions throughout the technology life cycles that occurred between 1995 and 2017.

Our findings are based on the IV estimates, which are primarily reported in Tables 2 and 3. These tables present the impact of digital technology exposure on the employment-to-population ratio and average wage, respectively. We also report several complementary tables, including the first-stage regressions and heterogeneity analysis by clusters of regions, in the appendix.[26]

Table 2: Impact of Digital Technologies on the Employment-to-Population Ratio

	IV Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	0.11^{***}	0.31^{***}	0.01	-0.03	0.01	0.07^{**}
	(0.03)	(0.07)	(0.11)	(0.06)	(0.04)	(0.03)
ICT Exposure	0.05^{***}	0.62^{***}	-0.71^{***}	-0.01	-0.10^{***}	-0.00
	(0.02)	(0.12)	(0.27)	(0.05)	(0.04)	(0.03)
SDB Exposure	-0.06^{***}	-0.37^{***}	0.38^{**}	-0.00	0.10^{***}	0.00
	(0.02)	(0.11)	(0.19)	(0.05)	(0.03)	(0.03)
R^2	0.61	0.64	0.64	0.66	0.92	0.82
Num. obs.	158	158	158	158	158	158
F statistic	13.00	14.92	14.85	16.07	90.92	36.31

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage point change in the regional employment-to-population ratio to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

[26]Tables C.1, C.2, and C.3 present the estimates from the OLS regressions for the change in employment, employment-to-population ratio, and average wage. Tables C.4 to C.6 show the results of the first stage. We observe a strong correlation between investment in the three digital technologies in the European regions and the U.S. The coefficients are always significant, and the F-statistic is high, with the exceptions of the second phase of the GUI & Cloud and the second phase of Web 1.0 for software and databases. Table C.7 summarizes the IV estimate for the log-change in employment. Tables C.8 to C.13 present the regional cluster coefficients, estimated separately to highlight the heterogeneity in the relationship between the primary variables.

Table 3: Impact of Digital Technologies on the Average Wage

	IV Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	0.00	-0.37	-0.01	-0.23	0.55^{***}	0.40^{***}
	(0.12)	(0.23)	(0.23)	(0.15)	(0.10)	(0.08)
ICT Exposure	-0.23^{***}	-1.43^{***}	0.78	0.06	-0.03	0.26^{***}
	(0.07)	(0.38)	(0.58)	(0.14)	(0.09)	(0.09)
SDB Exposure	0.26^{***}	1.09^{***}	-0.16	0.14	0.02	0.12
	(0.08)	(0.34)	(0.41)	(0.12)	(0.08)	(0.07)
R^2	0.66	0.50	0.82	0.67	0.89	0.65
Num. obs.	158	158	158	158	158	158
F statistic	15.71	8.31	36.29	16.82	68.66	15.02

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized log-change in average wage over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the regional average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

5.1 Short-term *versus* Long-term Impacts

Employment. Table 2 shows significant short-term positive and negative (annualized) impacts of all groups of digital automation technologies on the regional employment-to-population ratio for several phases of their technology life cycles. These short-term effects are substantially larger than the effect over the long term. In the case of ICT and SDB, this is because short-term negative and positive effects cancel out in the long term. In the case of robots, this is because the positive effects are concentrated in only two phases of the technology life cycle.

For ICT, a 1-STD increase in regional exposure over the period 1995–2017 implies a 0.05 percentage point (pp.) annual increase in the employment-to-population ratio. This translates into an overall 1.1 pp. increase over the 22 years. This small positive change over the long term is a combination of negative and positive impacts in different phases of the technology life cycle. In the first phase of the Web 1.0 technology cycle, a 1-STD increase in regional exposure generates a 0.62 pp. annual increase in the employment-to-population ratio, which is 3.72 pp. over the 6 years of this cycle. This positive impact is almost entirely offset by the 0.71 pp. annual decrease in the second phase of the same cycle (i.e., -2.13 pp. over 3 years) and the 0.1 pp. decrease during the second phase of the GraphUI-Cloud technology life cycle (i.e.,

-0.4 pp. over 4 years).

We find similar results for SDB but with the opposite sign. The small annual negative impact on the employment rate (-0.06 pp.) translates into an overall impact of -1.32 pp. over 22 years. However, this result hides a much larger negative impact in the first phase of the Web 1.0 technology life cycle, with a decline of 2.22 pp. over six years, balanced by a positive impact of the same magnitude during the second phase.

The pattern for robots differs in two main respects. First, in the case of robots, we do not find that positive and negative impacts cancel out. In fact, robot exposure only shows positive impacts on the regional employment-to-population ratio. However, the overall positive effect on the employment-to-population ratio of 0.11 pp. (annualized) for a 1-STD increase in robot exposure, which corresponds to a 2.42 pp. increase over the entire period, is concentrated almost entirely in the first phase of the Web 1.0 technology life cycle. During this phase, a 1-STD increase in robot exposure at the regional level brings about an annual change of 0.31 pp. in the employment rate. In the remaining phases, the effect is not statistically significant, except in the first phase of the Big Data and AI cycle, when it is small.

Average wage. Turning to the effects on average wages, we also find different impacts for ICT, SDB, and robots. In the short term, we find that robots have a significant positive impact on wages, but only in the last two phases (i.e., 2009–2013 and 2013–2017). These are not enough to show up in the long-term differences in wages in regions that are more exposed to robots.

For both ICT and SDB, their long-term impacts seem to be driven by the first phase of the Web 1.0 cycle between 1995 and 2001. A 1-STD increase in regional exposure to ICT leads to an annual decline in the average wage of about 0.23 pp., whereas the same increase in regional exposure to SDB generates a 0.26 pp. increase. We also find a positive effect of ICT in the Big Data and AI cycle, with a 1-STD increase in regional exposure generating a 0.26 pp. increase in the average wage.

Heterogeneity across regions. We study how results vary for different types of regions, based on their historical sectoral specialization and labor productivity (Tables C.8 to C.13). We find differences between ICT, SDB, and robots.

The positive impact of robots on employment over the long term occurs in all types of regions, regardless of their structural characteristics. The sign of the effect is similar across regions also for most phases of the three technology cycles.

Conversely, ICT and SDB show different patterns across different regions. For ICT, the positive impact on the employment-to-population ratio observed over the long term is driven by industry-specialized regions. However, these regions do not drive the short-term impacts.

In the short term, we observe that service-specialized regions experience the most significant impacts, both economically and statistically. In service-oriented regions, the negative and positive short-term impacts on the employment rate cancel out in the long term; whereas in industry-oriented regions, we observe positive impacts in all phases of the three technology cycles—although only significant in the last cycle. This result confirms the relevance of distinguishing between short-term effects and what we observe in the long term.

We observe fewer differences in the impact of ICT on the employment rate between high- and low-productivity regions. The short-term effects are more significant in highly productive regions, where they also do not completely cancel out over the long term.

In sum, highly productive regions relatively more specialized in industry drive the long-run results, but it is in highly productive regions relatively more specialized in services that ICT has a significant impact on the employment rate in the short term. The same holds for the short-term impact on wages.

Concerning SDB, the impact of higher exposure on the employment-to-population ratio over the long term is similar for regions with different sector specializations. However, this similarity hides important short-term differences. In the case of agriculture- and industry-specialized regions, we find no short-term impact on the employment rate. The short-term average impact is driven by service-specialized regions.

We also find that short-term effects do not completely cancel out in the long term in high-productivity regions, resulting in a negative long-run impact on the employment rate.

In sum, similarly to ICT, highly productive regions relatively more specialized in services drive the impacts on employment and wages in the short term.

5.2 The Role of Technology Life Cycles

Our results, as highlighted in Table 2, show that the technology life cycle influences the impact of automation on the regional employment rate differently for various groups of technologies (i.e., ICT, SDB, and robots).

We find two opposite patterns for the impact of ICT and SDB on the employment-to-population ratio. In the case of ICT, a substitution effect dominates in the *second phase* of the technology life cycle, when the most exposed regions experience a reduction in the employment-to-population ratio. This occurs when the technology is more mature and standardized, firms have learned to integrate it more efficiently into the production process, and the routinization of tasks is better codified. In the *first phase*, the impact on the employment-to-population ratio is either positive (first technology cycle) or nil (second and third technology cycles).[27]

[27] It should be noted that both the first and the third cycles are truncated in our data. It may be that the first phase of the first cycle starts before what we observe in our data.

Looking at Tables C.8 and C.13, which present heterogeneous results by type of region (distinguished by sector specialization and labor productivity), we find that this pattern holds particularly for high-productivity regions that are relatively more specialized in services. Specifically, these are regions specialized in knowledge-intensive services, primarily densely populated urban areas, as suggested by Figures D.1 and D.2.

In the case of SDB, a complementary effect dominates in the *second phase* of the technology life cycle: the most exposed regions experience an increase in the employment-to-population ratio. This may be because the adoption of the technology by early adopters leads to production expansion, thereby increasing demand for workers during the more mature stages of the technology life cycle. In the *first phase*, the impact on the employment-to-population ratio is either negative (first technology cycle) or nil (second and third technology cycles).

Similarly to ICT, this pattern holds only for regions that are relatively more specialized in services and are more productive (Tables C.8 and C.13). In low-productivity regions, we observe a significant impact on the employment rate only in the first phase, which is negative in the first cycle and positive in the second cycle.

For robots, we do not find any regularity between phases of the three technology life cycles. The impact on the employment-to-population ratio varies by technological breakthrough. It is positive in the first and third technology life cycles, but not in the second one. The impact is positive in the first phase of the first and third technology life cycles;[28] while we do not observe any effect in the first phase of the second technology life cycle.

These regularities do not appear when examining the impacts of the three groups of technologies on the average wage.

6 Conclusion

This paper examines the impact of labor market exposure to several vintages of robots, ICT, and software and database (SDB) in 163 European regions across 12 countries from 1995 to 2017. We identify new vintages in digital technologies, marked by breakthrough innovations, and demonstrate their correlation with periods of acceleration and deceleration in investment trends. We focus on the short-term impacts of these technologies on labor market outcomes, specifically the employment-to-population ratio and average wage, during the acceleration and deceleration phases of the technology life cycles. We use corresponding US investments as instruments for European investment in these technologies.

Our study finds evidence of significant positive and negative impacts in the short term during the technology life cycle phases, although the effects of robots, ICT, and SDB on the

[28] However, for the third life cycle, we do not observe the second phase, and the first phase may be truncated.

employment-to-population ratio over the long term are small. These small long-term effects result from short-term effects that offset each other along the technology life cycles. For instance, regions more exposed to ICT investments experience an increase in labor demand during the early phases, offset by a decline during the mature phases. Conversely, higher SDB investment reduces labor demand during the early phases and increases it during the mature phases. When regions are exposed to both ICT and SDB, these effects tend to cancel out even in the short term.

However, we find that the long-term positive impact of robots on the employment-to-population ratio is driven by two specific periods: 1995–2001 and 2013–2017. We do not find negative effects on employment, suggesting that short-term perspectives may explain the heterogeneous results in the literature on the impact of robots on European employment. The differences found in prior work may be due to the varying impacts of different robot vintages on the labor market.

Lastly, we find that regional structural differences, such as labor productivity and employment specialization, do not influence the impact of robots on labor market outcomes. However, these differences do affect the impact of ICT and SDB. Specifically, the effects of ICT and SDB are driven by highly productive regions specialized in services, such as densely populated urban areas.

The main implication of our study is that policy should address the short-term effects of automation, which vary among technologies and different phases of their life cycles. While new job creation is a long-term effect driven by productivity gains and new goods and services, short-term policies are needed to support workers adversely affected by automation. Specifically, policies should mitigate the short-term negative effects on employment seen in the mature phases of ICT investments and the early phases of SDB investments. Additionally, it is crucial to address the long-term negative consequences of ICT exposure on wages, which may increase inequality. Labor market institutions could play an important role in alleviating these adverse effects, particularly in densely populated urban areas.

Our study has some limitations, suggesting directions for future research. The main limitation is the lack of data on the adoption of specific technologies across countries and regions. While we consider country-specific differences in exposure to technology, our approach assumes uniform adoption of the same technology vintage across all European regions. Additionally, our analysis cannot differentiate between early and late-adopting firms within a region. These limitations highlight the need for more comprehensive comparative studies of countries and regions, using comparable firm-level and employee data. Moreover, given the varying impacts of these technologies on different worker types, a task-based approach could provide insights into whether different technology life cycles significantly affect workforce composition.

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Appendices

A Data

Sector aggregation We consider six sectors as the result of the aggregation and compatibilization between NACE Rev. 1.1 and Rev. 2. Agriculture (A) corresponds to activities that relate to agriculture, forestry, and fishing. Industry (B-E) refers to manufacturing, mining and quarrying, utilities; except Construction (F) which is a sector in itself. Market Services (G-J) encompass service activities such as wholesale and retail trade, accommodation and food service activities, transportation and storage, along with information and communication. Financial & Business Services (K-N) correspond to financial and insurance activities; real estate activities; professional, scientific, technical, administration and support service activities. Lastly, Non-Market Services (O-U) regroup all other services such as public administration and defense, education, human health and social work activities; and any other service activities.

Table A.1 summarizes the aggregation of sectors by providing the corresponding sections in both revisions of the NACE classification. Table A.2 presents the overview of both revisions of the NACE classification and the correspondence.

Table A.1: Sectors of economic activities and NACE sections

	Sector	NACE Rev. 2	NACE Rev. 1.1
A	Agriculture	A	A, B
B-E	Industry	B, C, D, E	C, D, E
F	Construction	F	F
G-J	Market Services	G, I, H, J	G, H, I
K-N	Financial Business Services	K, L, M, N	J, K
O-U	Non-Market Services	O, P, Q, R, S, T, U	L, M, N, O, P, Q

Notes: This table presents the classification of 1-digit NACE industries into sectors used in the analysis. The classification is derived from the NACE classifications to be compatible across the two versions Rev. 1.1 and Rev. 2. Table A.2 summarizes both NACE classifications in the appendix.

Table A.2: Overview of NACE classifications

NACE Rev. 2		NACE Rev. 1.1	
A	Agriculture, forestry and fishing	A	Agriculture, hunting and forestry
		B	Fishing
B	Mining and quarrying	C	Mining and quarrying
C	Manufacturing	D	Manufacturing
D	Electricity, gas, steam and air conditioning supply	E	Electricity, gas and water supply
E	Water supply, sewerage, waste management and remediation activities		
F	Construction	F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	G	Wholesale and retail trade: repair of motor vehicles, motorcycles and personal and household goods
I	Accommodation and food service activities	H	Hotels and restaurants
H	Transportation and storage	I	Transport, storage and communications
J	Information and communication		
K	Financial and insurance activities	J	Financial intermediation
L	Real estate activities	K	Real estate, renting and business activities
M	Professional, scientific and technical activities		
N	Administrative and support service activities		
O	Public administration and defence; compulsory social security	L	Public administration and defence; compulsory social security
P	Education	M	Education
Q	Human health and social work activities	N	Health and social work
R	Arts, entertainment and recreation	O	Other community, social and personal services activities
S	Other service activities		
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	P	Activities of private households as employers and undifferentiated production activities of private households
U	Activities of extraterritorial organisations and bodies	Q	Extraterritorial organisations and bodies

Notes: This table presents the correspondence between the two revisions (Rev. 2. and Rev. 1.1) of the NACE classification.

B Descriptive Statistics

Table B.1 shows the number of regions in each cluster and their centers (within-cluster averages).

Table B.1: Clusters and K-means

	Cluster	N	K-means		
			Agriculture	Industry	Service
1	Industry intensive	72	-0.29	0.85	-0.47
2	Agriculture intensive	47	1.17	-0.47	-0.47
3	Service intensive	44	-0.77	-0.90	1.27

Notes: This table presents the clusters, the number of regions in each group, and their within-cluster average in clustering variables. N is the number of regions in the cluster. The clustering variables are expressed in standard deviation. Agriculture, Industry, and Service represent the regional share of employment in these sectors, which are standardized at the country level.

Table B.2 shows the summary statistics of the change in the outcome variables, in the technology stock (per thousand workers in 1980), as well as in imports and final demand, over the whole period of analysis (1995–2017).

Table B.2: Summary Statistics of Long Run Change in Variables (1995–2017)

Variable	Mean	SD	Min	Q1	Q2	Q3	Max	N
Emp	0.8	0.6	-0.2	0.5	0.8	1.1	2.6	158
Emp-to-pop	0.2	0.1	-0.3	0.1	0.2	0.3	0.6	158
Wage	0.7	0.6	-0.5	0.3	0.6	1.0	2.5	158
ROB	0.0	1.0	-1.2	-0.7	-0.3	0.4	2.9	158
ICT	0.0	1.0	-1.2	-0.8	-0.5	0.8	3.2	158
SDB	0.0	1.0	-1.4	-0.8	-0.3	0.6	3.2	158
Imports	2.0	0.8	0.4	1.4	1.9	2.7	3.9	158
Final demand	5.0	7.2	-8.0	-0.4	5.0	8.0	42.0	158

Notes: This table shows the summary statistics of the change in the outcome, independent, and control variables for the 163 NUTS-2 regions between 1995 and 2017. Outcomes variables are employment, employment-to-population ratio (Emp-to-pop. ratio)—measured as the total number of employed persons aged 15-64 over the total population—, average yearly wage per worker (Wage) in thousands euros of 2015—calculated as the ratio between total labor compensation and the level of employment. All outcome variables are annualized (this is, divided by the number of years in the period). Data are from the ARDECO database. Independent variables are technology stock (per thousand workers in 1980) in robots (ROB), communication and information technology (ICT), and software and database (SDB). Data are from the IFR for robots and EU-KLEMS for the rest. Control variables are imports—measured as imports from China using the OECD Trade in Value Added database—and final demand—measured as the real consumption index from the Inter-Country Input-Output database.

Tables B.3 and B.4 show the summary statistics for technology stock (per thousand workers in 1980) by, respectively, region specialization and productivity level. Regions are grouped into three categories for specialization: agriculture-intensive, industry-intensive and service-intensive regions.

Table B.3: Summary Statistics for by Region Specialization (change in technology exposure 1995-2017)

Tech	Cluster	Mean	SD	Min	Q1	Q2	Q3	Max	N
ROB	Service	-0.28	0.83	-1.25	-0.77	-0.52	-0.23	1.87	46
	Industry	0.35	1.09	-1.21	-0.37	0.04	0.51	2.87	71
	Agriculture	-0.29	0.83	-1.23	-0.83	-0.65	-0.06	1.86	41
ICT	Service	0.32	1.04	-0.98	-0.58	0.10	1.06	3.24	46
	Industry	0.06	1.03	-1.02	-0.76	-0.41	0.81	2.41	71
	Agriculture	-0.47	0.71	-1.24	-0.86	-0.68	-0.48	1.40	41
SDB	Service	0.20	1.09	-1.25	-0.69	-0.12	0.80	3.24	46
	Industry	0.01	0.98	-1.29	-0.81	-0.39	0.58	2.20	71
	Agriculture	-0.24	0.89	-1.35	-0.93	-0.50	0.39	2.20	41

Notes: This table shows the summary statistics of the change in technology exposure in 1995-2017 by region specialization. The variables are technology stock (per thousand workers in 1980) in robots (ROB), communication and information technology (ICT), and software and database (SDB). Data are from the IFR for robots and EU-KLEMS for the rest. We apply a k-means clustering taking the regional employment share in 1980 in Agriculture, Industry and Services.

Table B.4: Summary Statistics for by Productivity Level (change in technology exposure 1995-2017)

Tech	Productivity	Mean	SD	Min	Q1	Q2	Q3	Max	N
ROB	High	0.15	1.07	-1.19	-0.58	-0.23	0.43	2.87	79
	Low	-0.15	0.91	-1.25	-0.77	-0.32	0.14	2.56	79
ICT	High	0.21	1.06	-1.00	-0.70	-0.10	1.28	3.24	79
	Low	-0.21	0.89	-1.24	-0.80	-0.57	0.10	2.41	79
SDB	High	0.03	1.02	-1.29	-0.77	-0.43	0.59	3.24	79
	Low	-0.03	0.99	-1.35	-0.87	0.00	0.53	2.52	79

Notes: This table shows the summary statistics of the change in technology exposure in 1995-2017 by producitivity level of the region. The variables are technology stock (per thousand workers in 1980) in robots (ROB), communication and information technology (ICT), and software and database (SDB). Data are from the IFR for robots and EU-KLEMS for the rest. We estimate labor productivity in 1980 by calculating the ratio between Gross Value Added (GVA) at constant prices and employment (in thousands) for each region. We categorize regions into the high (low) productivity group when their productivity level is above (below) the median (considering the entire sample of regions).

C Regressions

C.1 OLS Regressions

Table C.1: Impact of Automation Technologies on Employment (OLS Estimate)

	OLS Reg. - Dep. var.: Annualized Δ Employment (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	0.20^{***}	0.14	-0.44^{***}	0.01	0.13^{*}	-0.04
	(0.06)	(0.12)	(0.11)	(0.05)	(0.07)	(0.07)
ICT Exposure	0.07	-0.05	-0.54^{***}	0.20^{***}	-0.34^{***}	-0.00
	(0.05)	(0.11)	(0.12)	(0.05)	(0.13)	(0.07)
SDB Exposure	0.03	-0.06	0.08	0.07	-0.26^{***}	-0.17^{**}
	(0.06)	(0.12)	(0.11)	(0.04)	(0.10)	(0.08)
R^2	0.31	0.20	0.35	0.17	0.73	0.28
Num. obs.	158	158	158	158	158	158
F statistic	13.71	7.69	16.17	6.35	83.99	12.03

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized log-change in employment over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in regional employment to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.2: Impact of Automation Technologies on the Employment-to-Population Ratio (OLS Estimate)

	OLS Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	0.08^{***}	0.14^{***}	-0.16^{***}	-0.02	0.16^{***}	-0.12^{***}
	(0.02)	(0.04)	(0.05)	(0.03)	(0.02)	(0.03)
ICT Exposure	0.02^{*}	0.01	-0.15^{***}	0.09^{***}	-0.27^{***}	-0.02
	(0.01)	(0.04)	(0.05)	(0.03)	(0.05)	(0.03)
SDB Exposure	-0.01	0.04	-0.08^{*}	0.01	-0.16^{***}	-0.12^{***}
	(0.02)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)
R^2	0.35	0.22	0.18	0.29	0.85	0.46
Num. obs.	158	158	158	158	158	158
F statistic	16.68	8.80	6.87	12.20	167.24	26.08

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized change in employment-to-population ratio over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage point change in the regional employment-to-population ratio to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.3: Impact of Automation Technologies on the Average Wage (OLS Estimate)

	OLS Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	-0.18^{**}	-0.63^{***}	-0.63^{***}	-0.18^{**}	-0.07	0.51^{***}
	(0.07)	(0.12)	(0.11)	(0.07)	(0.07)	(0.06)
ICT Exposure	0.21^{***}	0.30^{***}	0.72^{***}	0.22^{***}	0.32^{**}	-0.18^{***}
	(0.05)	(0.11)	(0.12)	(0.06)	(0.14)	(0.06)
SDB Exposure	0.06	-0.23^{*}	-0.04	0.12^{**}	-0.23^{**}	0.28^{***}
	(0.07)	(0.12)	(0.10)	(0.06)	(0.10)	(0.07)
R^2	0.24	0.23	0.51	0.37	0.70	0.38
Num. obs.	158	158	158	158	158	158
F statistic	9.84	8.95	31.30	17.59	69.46	18.99

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized log-change in average wage over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the regional average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

C.2 First Stage IV Regressions

Table C.4: First-Stage IV Regression (Robots)

	First Stage IV Regression – Dep. var.: ROB Exposure					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
Intercept	-1.30^{***}	-0.49^{***}	-0.21^{***}	-0.12^{***}	-0.25^{***}	-0.22^{**}
	(0.31)	(0.09)	(0.04)	(0.04)	(0.09)	(0.09)
ROB Exposure (US)	1.71^{***}	3.15^{***}	2.12^{***}	1.32^{***}	1.12^{***}	1.16^{***}
	(0.13)	(0.20)	(0.14)	(0.09)	(0.22)	(0.13)
R^2	0.52	0.62	0.58	0.58	0.15	0.33
Num. obs.	158	158	158	158	158	158
F statistic	165.70	252.96	217.69	215.50	27.05	75.34

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for robots (ROB). The dependent variables represent the robot exposure of European regions in shift-share. Robot Exposure (US) is the instrument variable also constructed as a shift-share with the change in US stock per thousand workers. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Regressions are weighted by the population in 1980.

Table C.5: First-Stage IV Regression (ICT)

	First Stage IV Regression – Dep. var.: ICT Exposure					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
Intercept	-0.25	0.23^{*}	0.03	0.04	-0.21	-0.22^{**}
	(0.27)	(0.12)	(0.03)	(0.11)	(0.16)	(0.10)
ICT Exposure (US)	0.21^{***}	0.29^{***}	0.19^{***}	0.20^{***}	0.15^{**}	0.18^{***}
	(0.03)	(0.08)	(0.04)	(0.06)	(0.07)	(0.04)
R^2	0.24	0.07	0.11	0.08	0.03	0.14
Num. obs.	158	158	158	158	158	158
F statistic	49.57	12.04	18.59	13.20	4.52	25.51

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for information and communication technology (ICT). The dependent variables represent the ICT exposure of European regions in shift-share. ICT Exposure (US) is the instrument variable also constructed as a shift-share with the change in US stock per thousand workers. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Regressions are weighted by the population in 1980.

Table C.6: First-Stage IV Regression (Software & Database)

	First Stage IV Regression – Dep. var.: SDB Exposure					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
Intercept	-0.39	0.01	0.23^{***}	-0.24^{*}	-0.23^{*}	-0.16
	(0.45)	(0.14)	(0.04)	(0.12)	(0.14)	(0.11)
SDB Exposure (US)	0.55^{***}	0.55^{***}	0.23^{***}	0.67^{***}	0.48^{***}	0.60^{***}
	(0.07)	(0.10)	(0.08)	(0.09)	(0.10)	(0.07)
R^2	0.28	0.17	0.05	0.25	0.13	0.29
Num. obs.	158	158	158	158	158	158
F statistic	59.46	32.57	8.27	51.74	24.33	64.75

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for software and database (SDB). The dependent variables represent the SDB exposure of European regions in shift-share. SDB Exposure (US) is the instrument variable also constructed as a shift-share with the change in US stock per thousand workers. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Regressions are weighted by the population in 1980.

C.3 Second Stage IV Regressions

Table C.7: Impact of Automation Technologies on Employment

	IV Reg. - Dep. var.: Annualized Δ Employment (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exposure	0.66^{***}	0.59^{***}	0.34	0.26^{*}	0.17	0.10
	(0.11)	(0.18)	(0.23)	(0.15)	(0.11)	(0.08)
ICT Exposure	0.34^{***}	1.60^{***}	-1.65^{***}	0.36^{***}	0.07	0.11
	(0.06)	(0.29)	(0.57)	(0.13)	(0.09)	(0.08)
SDB Exposure	-0.30^{***}	-0.89^{***}	0.78^{*}	-0.16	0.27^{***}	0.09
	(0.07)	(0.26)	(0.40)	(0.12)	(0.08)	(0.07)
R^2	0.69	0.70	0.78	0.34	0.89	0.73
Num. obs.	158	158	158	158	158	158
F statistic	18.25	19.01	29.30	4.21	64.41	22.17

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized log-change in employment over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in regional employment to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

C.4 Regional Cluster IV Regressions by Specialization

Table C.8: Impact of Automation Technologies on Employment by Specialization (Second Stage)

	IV Reg. - Dep. var.: Annualized Δ Emp. (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ Service	0.54^{***}	0.62^{**}	-0.09	0.13	0.04	0.16
	(0.16)	(0.29)	(0.25)	(0.22)	(0.14)	(0.14)
ROB Exp. $\times$ Industry	0.58^{***}	0.60^{***}	-0.11	0.21	0.21	0.12
	(0.12)	(0.23)	(0.23)	(0.16)	(0.13)	(0.12)
ROB Exp. $\times$ Agriculture	0.60^{***}	-0.21	-0.59	0.33	0.30	0.35^{**}
	(0.15)	(0.35)	(0.37)	(0.24)	(0.18)	(0.15)
ICT Exp. $\times$ Service	0.11	1.34^{***}	-2.58^{***}	0.05	-0.27^{**}	0.03
	(0.09)	(0.35)	(0.59)	(0.18)	(0.11)	(0.11)
ICT Exp. $\times$ Industry	0.45^{***}	1.09^{**}	0.75	0.29	0.36^{**}	0.25^{*}
	(0.12)	(0.50)	(0.74)	(0.24)	(0.16)	(0.15)
ICT Exp. $\times$ Agriculture	0.32	-0.70	2.59^{**}	-0.34	-0.31	-0.22
	(0.27)	(1.00)	(1.17)	(0.46)	(0.32)	(0.29)
SDB Exp. $\times$ Service	-0.22^{***}	-1.04^{***}	1.85^{***}	0.01	0.29^{***}	0.10
	(0.08)	(0.29)	(0.44)	(0.14)	(0.09)	(0.08)
SDB Exp. $\times$ Industry	-0.39^{***}	-0.72	-1.05^{*}	-0.30	0.02	0.07
	(0.14)	(0.51)	(0.60)	(0.22)	(0.16)	(0.16)
SDB Exp. $\times$ Agriculture	-0.17	1.61^{*}	-2.74^{**}	0.53	0.61^{**}	0.38
	(0.26)	(0.91)	(1.11)	(0.45)	(0.28)	(0.25)
R^2	0.72	0.74	0.84	0.40	0.91	0.75
Num. obs.	158	158	158	158	158	158
F statistic	13.62	15.06	28.53	3.59	50.72	15.61

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the Regional Cluster IV regressions where the outcome variable is the annualized log-change in employment over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in regional employment to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.9: Impact of Automation Technologies on the Employment-to-Population Ratio by Specialization (Second Stage)

	IV Reg. - Dep. var.: Annualized Δ Emp-to-pop. $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ Service	0.11^{**}	0.43^{***}	-0.13	-0.04	-0.00	0.13^{**}
	(0.05)	(0.12)	(0.12)	(0.09)	(0.06)	(0.05)
ROB Exp. $\times$ Industry	0.12^{***}	0.32^{***}	-0.16	0.02	-0.00	0.07
	(0.04)	(0.09)	(0.11)	(0.07)	(0.05)	(0.04)
ROB Exp. $\times$ Agriculture	0.10^{**}	0.02	-0.41^{**}	0.04	0.01	0.15^{***}
	(0.05)	(0.14)	(0.18)	(0.10)	(0.08)	(0.05)
ICT Exp. $\times$ Service	-0.01	0.64^{***}	-1.02^{***}	-0.08	-0.20^{***}	-0.01
	(0.03)	(0.14)	(0.28)	(0.08)	(0.05)	(0.04)
ICT Exp. $\times$ Industry	0.08^{**}	0.30	0.46	-0.09	0.02	0.14^{**}
	(0.04)	(0.20)	(0.36)	(0.10)	(0.07)	(0.05)
ICT Exp. $\times$ Agriculture	0.05	-0.19	1.44^{**}	-0.13	-0.04	-0.08
	(0.08)	(0.40)	(0.57)	(0.19)	(0.13)	(0.10)
SDB Exp. $\times$ Service	-0.04^{*}	-0.51^{***}	0.78^{***}	0.02	0.11^{***}	0.04
	(0.02)	(0.12)	(0.21)	(0.06)	(0.03)	(0.03)
SDB Exp. $\times$ Industry	-0.08^{*}	-0.20	-0.43	-0.01	0.07	-0.07
	(0.04)	(0.21)	(0.29)	(0.09)	(0.06)	(0.06)
SDB Exp. $\times$ Agriculture	-0.04	0.43	-1.43^{***}	-0.02	0.05	0.06
	(0.08)	(0.37)	(0.54)	(0.19)	(0.12)	(0.09)
R^2	0.65	0.70	0.74	0.69	0.93	0.84
Num. obs.	158	158	158	158	158	158
F statistic	9.94	12.09	14.93	11.57	66.99	27.79

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage point change in the regional employment-to-population ratio to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.10: Impact of Automation Technologies on the Average Wage by Specialization (Second Stage)

	IV Reg. - Dep. var.: Annualized Δ Avg. wage (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ Service	0.31^{*}	0.14	0.45	0.22	0.40^{***}	0.43^{***}
	(0.18)	(0.40)	(0.28)	(0.23)	(0.14)	(0.15)
ROB Exp. $\times$ Industry	0.13	0.01	0.16	-0.21	0.67^{***}	0.46^{***}
	(0.14)	(0.31)	(0.26)	(0.17)	(0.13)	(0.12)
ROB Exp. $\times$ Agriculture	0.19	0.17	0.52	-0.05	0.69^{***}	0.54^{***}
	(0.17)	(0.48)	(0.42)	(0.25)	(0.18)	(0.16)
ICT Exp. $\times$ Service	-0.08	-1.21^{**}	1.66^{**}	0.15	0.12	0.18^{*}
	(0.11)	(0.48)	(0.66)	(0.19)	(0.11)	(0.11)
ICT Exp. $\times$ Industry	-0.26^{*}	-0.59	-0.29	0.10	-0.46^{***}	0.40^{**}
	(0.14)	(0.69)	(0.83)	(0.25)	(0.16)	(0.15)
ICT Exp. $\times$ Agriculture	-0.07	-0.45	-1.15	1.06^{**}	0.15	0.20
	(0.31)	(1.37)	(1.33)	(0.49)	(0.31)	(0.30)
SDB Exp. $\times$ Service	0.19^{**}	1.10^{***}	-1.04^{**}	0.09	-0.04	0.13
	(0.09)	(0.40)	(0.50)	(0.15)	(0.08)	(0.08)
SDB Exp. $\times$ Industry	0.29^{*}	0.65	0.90	0.09	0.20	-0.04
	(0.16)	(0.70)	(0.67)	(0.23)	(0.15)	(0.17)
SDB Exp. $\times$ Agriculture	-0.02	-0.10	1.42	-0.80^{*}	0.03	0.10
	(0.30)	(1.24)	(1.26)	(0.48)	(0.27)	(0.26)
R^2	0.68	0.54	0.84	0.70	0.91	0.66
Num. obs.	158	158	158	158	158	158
F statistic	11.41	6.11	27.92	12.41	53.25	10.18

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized log-change in average wage over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the regional average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

C.5 Regional Cluster IV Regressions by Productivity

Table C.11: Impact of Automation Technologies on Employment by Productivity

	IV Reg. - Dep. var.: Annualized Δ Emp. (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ High Prod.	0.57^{***}	0.52^{**}	0.11	0.15	-0.00	0.04
	(0.12)	(0.20)	(0.23)	(0.16)	(0.13)	(0.10)
ROB Exp. $\times$ Low Prod.	0.64^{***}	0.65^{**}	-0.17	0.33^{**}	0.17	0.23^{**}
	(0.13)	(0.25)	(0.26)	(0.17)	(0.13)	(0.11)
ICT Exp. $\times$ High Prod.	0.28^{***}	1.18^{***}	-2.18^{***}	0.36^{**}	-0.12	-0.00
	(0.10)	(0.39)	(0.58)	(0.17)	(0.12)	(0.11)
ICT Exp. $\times$ Low Prod.	0.41^{***}	1.86^{***}	-0.35	-0.01	0.18	0.30^{**}
	(0.12)	(0.51)	(0.82)	(0.23)	(0.16)	(0.13)
SDB Exp. $\times$ High Prod.	-0.33^{***}	-0.33	0.95^{**}	-0.38^{**}	0.26^{**}	0.13
	(0.12)	(0.38)	(0.47)	(0.18)	(0.13)	(0.12)
SDB Exp. $\times$ Low Prod.	-0.33^{***}	-1.24^{***}	-0.31	0.18	0.20^{*}	-0.02
	(0.10)	(0.46)	(0.65)	(0.18)	(0.11)	(0.10)
R^2	0.70	0.71	0.81	0.41	0.89	0.74
Num. obs.	158	158	158	158	158	158
F statistic	14.93	15.86	27.91	4.44	55.02	18.77

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the Regional Cluster IV regressions where the outcome variable is the annualized log-change in employment over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in regional employment to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.12: Impact of Automation Technologies on the Employment-to-Population Ratio by Productivity (Second Stage)

	IV Reg. - Dep. var.: Annualized Δ Emp-to-pop. $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ High Prod.	0.09^{**}	0.28^{***}	-0.13	-0.02	-0.03	0.04
	(0.04)	(0.08)	(0.11)	(0.06)	(0.05)	(0.04)
ROB Exp. $\times$ Low Prod.	0.12^{***}	0.36^{***}	-0.15	0.01	-0.00	0.10^{**}
	(0.04)	(0.10)	(0.13)	(0.07)	(0.05)	(0.04)
ICT Exp. $\times$ High Prod.	0.05^{*}	0.41^{***}	-0.85^{***}	0.09	-0.15^{***}	0.05
	(0.03)	(0.15)	(0.28)	(0.07)	(0.05)	(0.04)
ICT Exp. $\times$ Low Prod.	0.00	0.48^{**}	-0.59	-0.33^{***}	-0.02	-0.04
	(0.04)	(0.20)	(0.39)	(0.09)	(0.07)	(0.05)
SDB Exp. $\times$ High Prod.	-0.08^{**}	-0.06	0.27	-0.17^{**}	0.09^{*}	-0.08^{*}
	(0.04)	(0.15)	(0.23)	(0.07)	(0.05)	(0.04)
SDB Exp. $\times$ Low Prod.	-0.02	-0.35^{**}	0.29	0.26^{***}	0.06	0.05
	(0.03)	(0.18)	(0.31)	(0.07)	(0.05)	(0.04)
R^2	0.63	0.69	0.69	0.71	0.92	0.84
Num. obs.	158	158	158	158	158	158
F statistic	11.12	14.31	14.39	15.84	74.95	33.32

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage point change in the regional employment-to-population ratio to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.13: Impact of Automation Technologies on the Average Wage by Productivity (Second Stage)

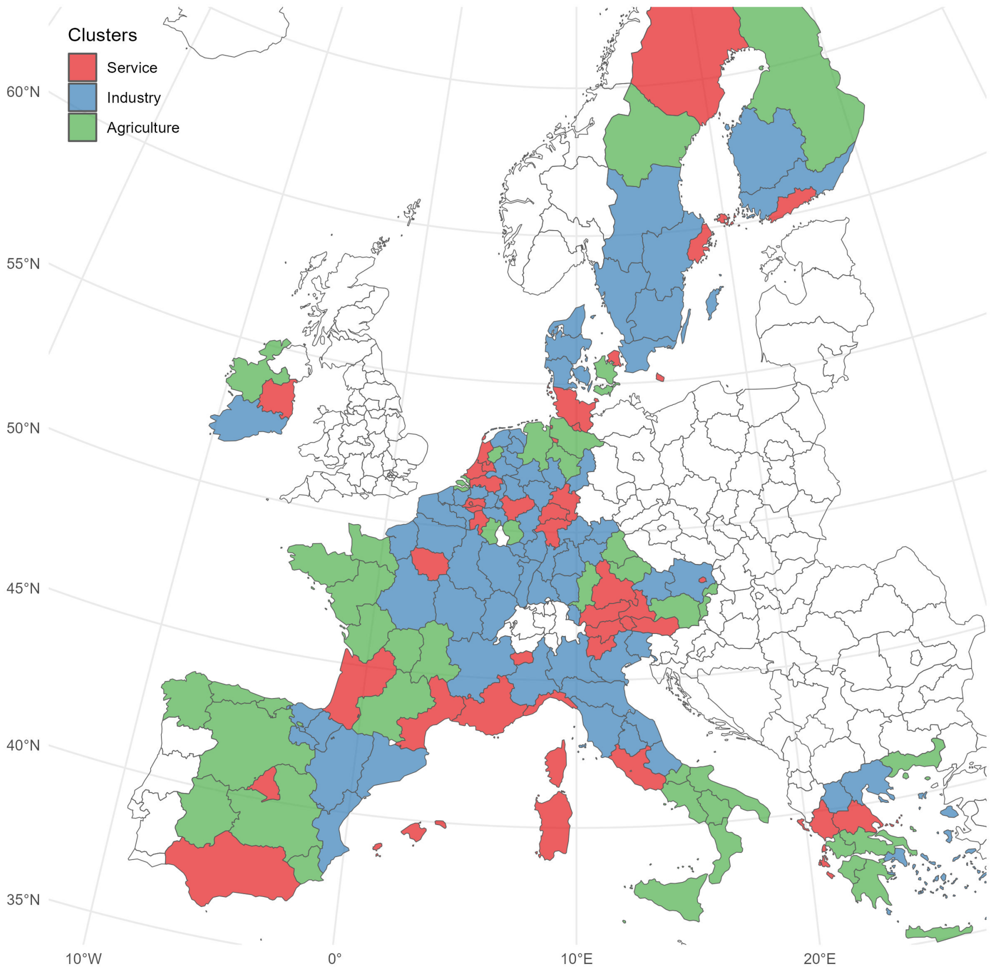
	IV Reg. - Dep. var.: Annualized Δ Avg. wage (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2001	2001-2004	2004-2009	2009-2013	2013-2017
ROB Exp. $\times$ High Prod.	0.16	-0.23	0.39	-0.21	0.58^{***}	0.40^{***}
	(0.13)	(0.26)	(0.24)	(0.16)	(0.12)	(0.11)
ROB Exp. $\times$ Low Prod.	0.10	-0.07	0.36	-0.37^{**}	0.54^{***}	0.49^{***}
	(0.14)	(0.32)	(0.27)	(0.17)	(0.12)	(0.11)
ICT Exp. $\times$ High Prod.	-0.20^{*}	-1.34^{***}	1.48^{**}	-0.08	0.02	0.15
	(0.11)	(0.51)	(0.59)	(0.18)	(0.12)	(0.11)
ICT Exp. $\times$ Low Prod.	-0.13	-0.58	0.23	0.29	-0.20	0.29^{**}
	(0.13)	(0.66)	(0.84)	(0.24)	(0.16)	(0.14)
SDB Exp. $\times$ High Prod.	0.39^{***}	1.06^{**}	-0.39	0.51^{***}	0.05	0.25^{**}
	(0.13)	(0.49)	(0.49)	(0.19)	(0.13)	(0.12)
SDB Exp. $\times$ Low Prod.	0.17	0.43	0.21	-0.14	0.09	0.06
	(0.11)	(0.59)	(0.67)	(0.19)	(0.11)	(0.10)
R^2	0.68	0.53	0.84	0.70	0.89	0.66
Num. obs.	158	158	158	158	158	158
F statistic	13.61	7.32	34.46	15.10	55.04	12.45

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized log-change in average wage over the cycle phase. Each column represents a phase of the digital cycle. The first column is the long-difference estimate for the entire period (1995–2017), the second and third columns correspond to the two phases of the Web 1.0 cycle, the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle, and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to robots (ROB), information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the regional average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

D Additional Figures

Figure D.1 shows the geographical distribution of regions according to our clustering strategy.

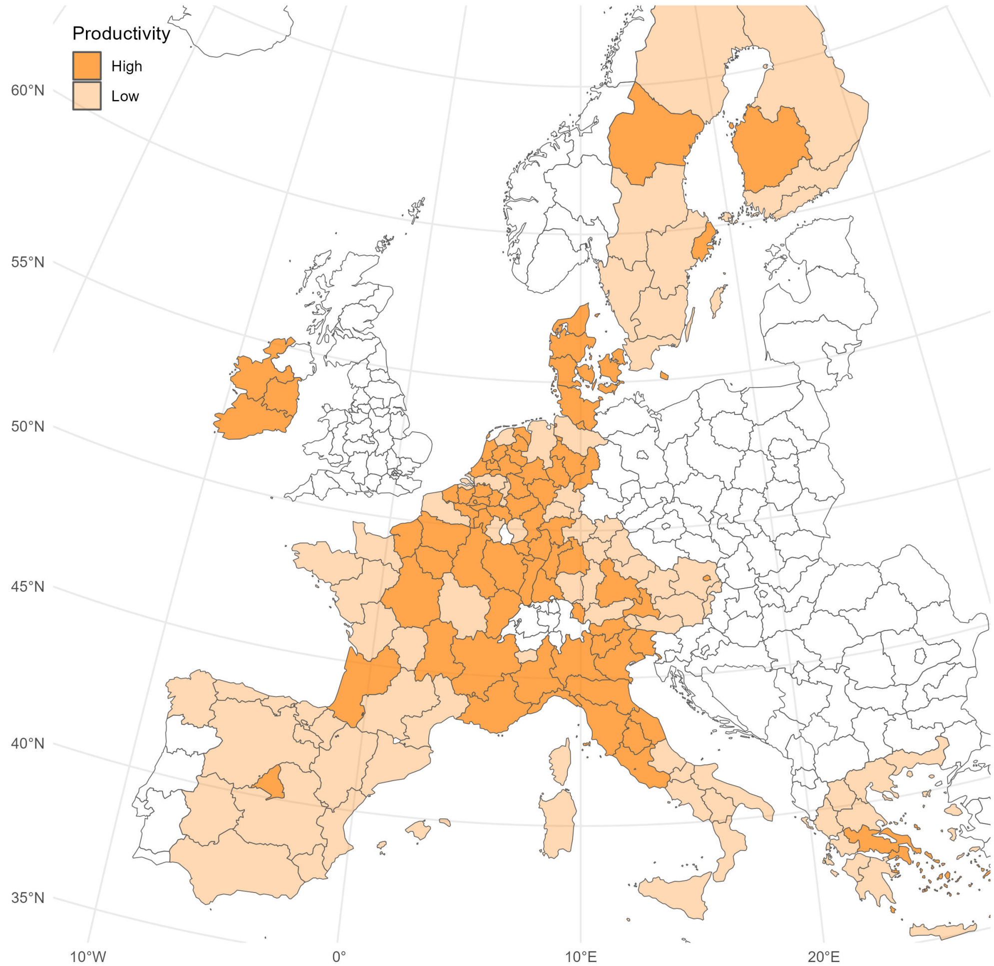
Figure D.1: Clusters of Regions According to Specialization



Notes: This figure presents the geographical distribution of the clusters. We compute the clusters by using a K-means algorithm. The variables employed for the clustering are the shares of employment in agriculture, industry, and services in 1980. We standardize the variables at the country level. The data on employment comes from the ARDECO database.

Figure D.2 shows the geographical distribution of regions according to their labor productivity level in 1980. Regions are categorized as 'High (Low)-productivity' if their productivity is above (below) the median of the entire sample of regions.

Figure D.2: Clusters of Regions According to Productivity

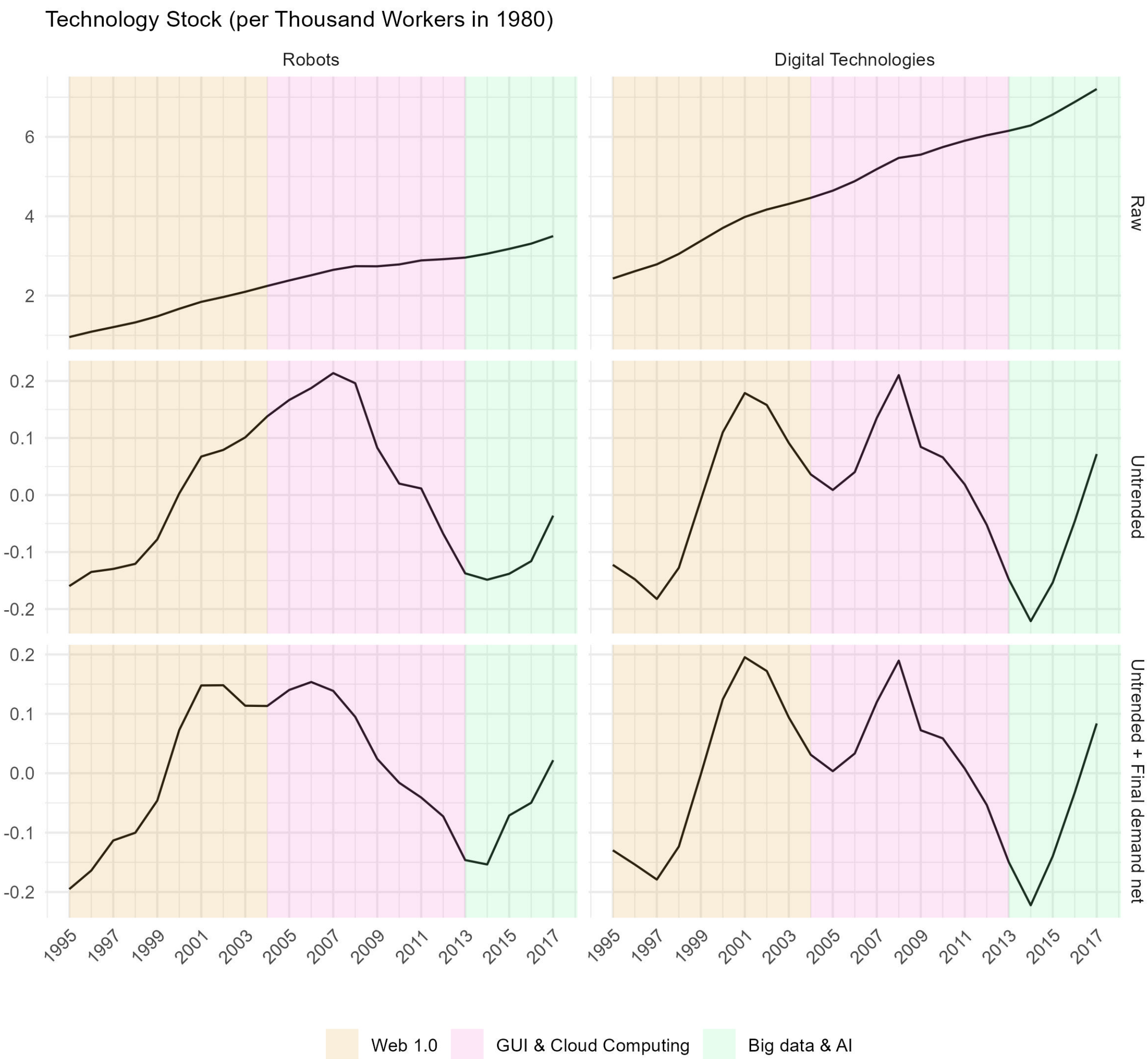


Notes: This figure presents the divide of regions according to their productivity level in 1980. We compute the clusters by using a K-means algorithm. The variables employed for the clustering are the shares of employment in agriculture, industry, and services in 1980. We standardize the variables at the country level. Labor productivity is estimated as the ratio between GVA at constant prices and employment (in thousands) in 1980 for each region. For Greece and Ireland, there is no information on GVA prior to 1995, therefore we have used this year for the computation in these two cases.

D.1 Technology Stocks

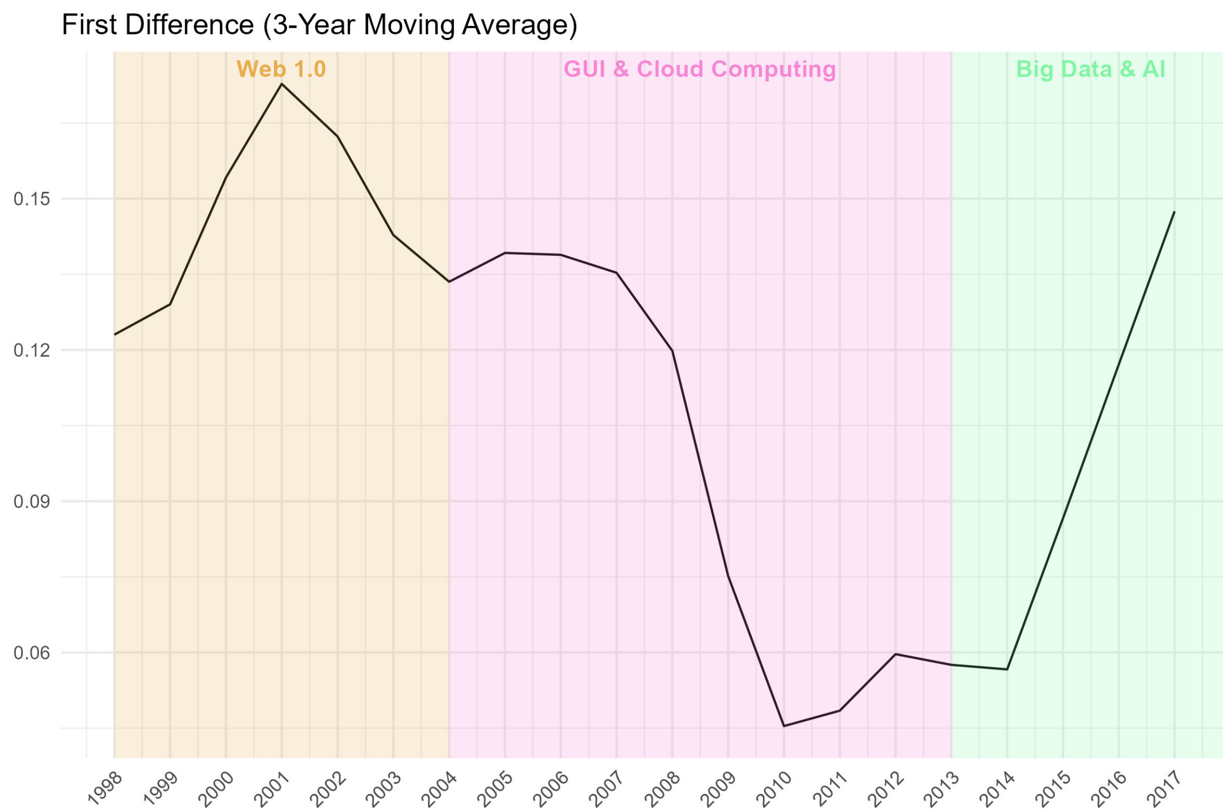
Figure D.3 presents the technology stocks (per thousand workers in 1980) from 1995 to 2017, expressed as an index, for robots, communication technology, information technology, and software and databases. The first row of panels displays the raw time series, which is increasing for all technologies. The second row of panels depicts the detrended variables, accounting for long-term patterns in technology investment. Lastly, the third row of panels further adjusts for the level of final demand, which could influence investment dynamics. Consequently, this row illustrates the investment in each technology, net of long-term trends and final demand dynamics.

Figure D.3: Technology Stocks per Thousand Workers in 1980



Notes: This figure shows the evolution of the technology stock per thousand workers in 1980 aggregated at the European level (this is, aggregated for the 12 European countries in the sample). Panel 'Raw' refers to the series in levels, panel 'Untrended' displays the residuals after regressing the Raw series on a liner time trend, and panel 'Untrended + Final demand net' shows the residuals after regressing the 'Raw' series on a liner time trend and on the real consumption (to account for business cycles). TLC stands for technology life cycles.

Figure D.4: Evolution of Robot Stock in First Difference (3-Year Moving Average)



Notes: This figure depicts the evolution of the first difference robot stock per thousand workers at the EU level (aggregated for the 12 European countries in the sample). The series is smoothed by taking the 3-year moving average.

Table E.1: Major Technological Developments during the Web 1.0 Cycle (1990–2004)

Computational power	1980s	Personal computers
	1993	Intel Pentium microprocessor (Intel)
Network communication	1990	HTML (Tim Berners Lee, CERN)
	1993	MOSAIC (Eric Bina, Marc Andreesen; University of Illinois)
	2000s	Diffusion of internet and digital infraestructure
Software	1990	Windows 3.0 (Microsoft)
	1991	LINUX (Linus Torvalds)
	1990s	Diffusion of World Wide Web (WWW)

Notes: Own elaboration based on Freeman and Louçã (2001), Mowery and Simcoe (2002), and Table 4 from Nuvolari (2020).

E Technological Cycles: Summarizing Major Developments

In this section, we summarize the major technological developments of digital automation technologies by technology cycles.

E.1 Web 1.0

Table E.1 outlines major technological developments during the Web 1.0 cycle (1990–2004). Advancements in mainframes and microcomputers began in the 1960s and 1970s. However, only with the reduction in price and size of microprocessors did personal computers become available for use in administrative tasks and smaller firms (Malerba et al. 1999, Freeman and Louçã 2001).[29] Concurrently, newer and more user-friendly operating systems like Windows 3.0 in 1990, Linux in 1991, and Windows 95 facilitated widespread adoption.

In contrast to previous decades when the Internet was confined to researchers and engineers, the number of Internet hosts significantly increased in the late 1990s (Mowery and Simcoe 2002). This surge was facilitated by firms adopting computer hardware, the development of the HTTP protocol and HTML language, and the introduction of browsers designed for reading HTML documents (Mowery and Simcoe 2002). HTML and HTTP, introduced in the 1990s, enabled multimedia content in web pages and cross-referencing sources, allowing quick access to numerous multimedia pages. This gave rise to the WWW in 1991. The MOSAIC and Netscape browsers, introduced in 1993 and 1995 respectively, simplified and standardized online document visualization.

By 2002, over 50% of firms with 10 or more employees were utilizing the Internet (Pilat 2005). The percentage varies by country, with Japan and the Scandinavian countries leading adoption, with almost all firms using the Internet. The dramatic diffusion of the Internet

[29] In the U.S., private fixed investment in IT grew by around 98% between 1970 and 1999 (Mowery and Simcoe 2002).

Table E.2: Major Technological Developments during the Graphical User Interface and Cloud Computing Cycle (2004–2013)

Web 2.0	2004	Flickr API
	2006	Facebook and Twitter API
	2008	AppStore
	2012	Google Play
Cloud Computing	2006	Elastic Compute Cloud Commercial Services (EC2)
	2010	Microsoft Azure

Notes: Own elaboration based on Lane (2019).

changed retail dynamics and gave rise to online commerce (Mowery and Simcoe 2002). Major online retail companies like Amazon and eBay started operating in 1995. By 2001, a significant percentage of companies in Europe were using the Internet for sales or purchases (Mowery and Simcoe 2002).

The adoption of ICT triggered significant changes to firms' organizational structures, affecting business organization, communication with customers and suppliers, and work practices. ICT replaced various easily codified and programmed activities while creating new tasks. Qualitative firm-level research provides evidence of these changes. For example, Autor et al. (2002) offer a case study of a U.S. bank adopting check imaging and OCR software. The technology automated check reading and made electronic checks available to all workers, leading to the reorganization of certain activities and more specialized employment. Before digitalization in 1994, check exception examination involved around 650 clerks, with one worker overseeing the entire process per check. After adopting OCR software, checks became accessible electronically to multiple workers simultaneously, resulting in specialized tasks related to processing overdrafts, implementing stop payment orders, and verifying signatures (Autor et al. 2002).

E.2 Graphical User Interface and Cloud Computing

Table E.2 outlines the major technological developments during the Graphical User Interface and Cloud Computing Cycle (2004–2013) Gradually, developments in the internet led to a new phase known as 'Web 2.0'. While there is no precise definition of Web 2.0, it encompasses various dimensions, including technological aspects like AJAX, RIA, and XML/DHTML; principles such as participation, collective intelligence, and a rich user experience; and applications and tools like Wikipedia, Flickr, and Mashups (Kim et al. 2009). This phase is characterized by the perception of the Internet as a collaborative platform where users actively contribute to the development and improvement of applications. Social media platforms developed APIs, becoming primary channels for connecting individuals (Lane 2019), facilitating the creation of new applications and services seamlessly integrated with social media. In 2007, Apple initiated the 'App Revolution' by launching its software development kit for third parties, allowing developers to create apps for the iPhone. The Apple App Store launched in 2008, followed by Google Play in 2012 (Crook 2018).

Another notable feature of this phase is the increasing data intensity of applications, where improvement is related to the number of users (O'Reilly 2007). Companies leverage vast amounts of data from social media to tailor advertising based on consumer preferences. Data analytics has shifted from structured data to unstructured data using natural processing methods (Lee 2017). Cloud computing became more widespread in the 2000s, with Amazon introducing its Elastic Compute Cloud (EC2) service for businesses in 2006. Private clouds became available in 2008, and in 2010, Microsoft and other companies launched more accessible, user-friendly, and affordable cloud computing services (Foote 2021).

According to Eurostat, by 2021 around 40% of EU enterprises were using cloud computing services, with varying intensity across countries. Over 60% of enterprises in Sweden, Finland, the Netherlands, and Denmark use cloud computing. For detailed figures, see the EUROSTAT website.

Increasing investment in cloud computing services suggests a negative association with IT capital and software investment. Firms' fixed capital in IT tends to decrease, while cloud services enable the growth of start-ups and small and medium-sized firms (Bloom and Pierri 2018, DeStefano et al. 2023). This outcome appears driven by the lower costs of cloud services compared to the high fixed costs of ICT investments, which represent a substantial entry barrier for new firms (Etro 2009). The creation of more smaller firms has positive consequences for employment. Since small and medium-sized firms tend to be associated with high employment growth, their emergence enabled by cloud computing services positively affects employment (Etro 2009, Bloom and Pierri 2018).

E.3 Big Data and Artificial Intelligence

Table E.3 presents the major advances in the ongoing Big Data & Artificial Intelligence cycle. The spread of IoT technology, enabling physical objects equipped with sensors to communicate and share data with computing systems through wired or wireless networks without human mediation, is revolutionizing data collection, sharing, and transfer (Lee 2017). Technologies such as Wireless Sensor Networks (WSN), Radio-frequency identification (RFID), Bluetooth, Near-field communication (NFC), and Long Term Evolution (LTE) connect objects to the Internet and each other, facilitating data exchange (Khanna and Kaur 2020). The IoT, along with social media, is becoming a major source of data generation, including images, videos,

Table E.3: Major Technological Developments during the Big Data & Artificial Intelligence Cycle (2013–)

Internet of Things	2013	IoT becomes more widespread due to hardware platforms
	2016	IoT products widely available in the market
Big Data & Data analytics	2013	Hadoop 2.0, Apache Spark, Apache Storm, Apache Samza
	2014	Apache Flink
	2015	Apache Apex
	2016	Zettabyte Era
Artificial Intelligence (ML & DL)	2014	VVGNet, GAN, and GoogleNet
	2015	ResNet
	2016	DenseNet
	2017	WGAN

Notes: Own elaboration based on Barnett (2016), Gupta and Rani (2019), Khanna and Kaur (2020), and Cao et al. (2018).

and audio (Lee 2017). This technology is pervasive across various sectors, including aerospace, defense, agroindustry, precision agriculture, automotives, pharmaceuticals, consumer goods, chemicals, and ICT (Andreoni et al. 2021). For a comprehensive review of IoT uses in different sectors, see Andreoni et al. (2021).

Based on the widespread internet penetration from the previous period, big data and data analytics have surged significantly. For instance, Gupta and Rani (2019) shows that research publications related to big data in 2017 increased 126-fold compared to 2011. This coincided with the creation of several big data processing platforms, widely available since 2013 through Apache (Gupta and Rani 2019). The Apache Software Foundation (ASF), a non-profit organization, provides open-source software. According to Gupta and Rani (2019), Apache Spark is one of the most popular systems for large-scale data processing, outperforming Hadoop by using in-memory processing rather than a file system (IBMCloudEducation 2021). Other platforms released in this period, like Apache Storm and Apache Samza, are used for real-time analytics, cybersecurity, threat detection, and performance monitoring (Gupta and Rani 2019). These platforms were developed by social media companies, such as BackType (Apache Storm) and LinkedIn (Apache Samza). The compound annual growth of social media analytics is projected to be 27.6% between 2015 and 2020 (Lee 2017).

AI is gaining increasing attention as a subset of computer science designed to train machines to perform cognitive activities associated with human intelligence, such as learning, problem-solving, and interaction (Brynjolfsson and McAfee 2014, Baruffaldi et al. 2020). The major components of AI are machine learning and deep learning, which rely on neural network techniques.

AI's ability to perform various functions has led to its application in several industries

(Cockburn et al. 2018) for tasks such as visual and speech recognition, predictive analysis, machine translation, information extraction, and system management/control (Vannuccini and Prytkova 2023, Calvino et al. 2022).

The main distinction between machine learning and information and communication technology (ICT) lies in that while computerization codifies pre-existing knowledge related to repetitive activities, machine learning enables machines to learn from examples to achieve specific outputs (Brynjolfsson and Mcafee 2017). This process involves supervised learning systems, where machines predict particular results based on inputs from large databases. Progress in machine learning is closely tied to big data and the development of new algorithmic techniques, highlighting the interdependence between these technologies. These techniques enhance predictive power using backpropagation with multiple layers and vast datasets (Cockburn et al. 2018). Examples of AI applications include medical diagnoses, where machines now achieve higher accuracy than humans, and legal activities, where computers scan and process extensive legal documents for trials (Frey and Osborne 2017). These examples demonstrate AI's capability to handle cognitive non-routine activities.

Overall, AI adoption among firms remains relatively low. Between 2016 and 2018, only 3.2% of firms in the U.S. were using or testing AI (Acemoglu et al. 2022). Additionally, research shows that adoption is more prevalent among larger and older firms (Zolas et al. 2021, Acemoglu et al. 2022).