Automation and Employment Over the Technology Life Cycle: Evidence from European Regions*

Florencia Jaccoud† Fabien Petit‡ Tommaso Ciarli§
Maria Savona¶

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Abstract

This paper analyzes how the impacts of ICT, Software & Databases, and Robots on European regional labor markets (1995–2017) vary across technology life cycle phases. Motivated by theories predicting shifting skill biases between early adoption and maturity, we first identify major technological breakthroughs and delineate their life cycle phases (early vs. maturity) based on investment growth patterns. Using a shift-share instrumental variable approach, we estimate phase-specific impacts of regional technology exposure on employment and wages. While confirming that effects differ significantly across phases, we find only partial support for standard skill-bias predictions during early adoption. Our results highlight the importance of analyzing dynamics within specific technology life cycles to understand the heterogeneous short-term labor market adjustments often obscured in aggregated long-run analyses.

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

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†Camerino University and UNU-MERIT, United Nations University. Email: jaccoud@merit.unu.edu.

‡University of Barcelona and University College London, CEPEO. Email: f.petit@ub.edu. Website: fabien-petit.com.

§UNU-MERIT, United Nations University and University of Sussex, SPRU. Email: ciarli@merit.unu.edu.

¶University of Sussex, SPRU and Luiss University. Email: m.savona@sussex.ac.uk.

1 Introduction

The codification of tasks and the skills required to work with new digital and automation technologies change with each technological breakthrough (Kogan et al. 2023, Prytkova et al. 2024) and over their technology life cycle (Langlois 2003, Vona and Consoli 2015, Ciarli et al. 2021). A technology life cycle encompasses the stages a technology goes through from its initial conception to its eventual decline. These stages typically include research and development, market introduction (early phase), growth, maturity and decline, each characterized by different rates of innovation, adoption, and ultimately, investment (Tushman and Anderson 1986). Focusing on the core shift in adoption dynamics, we distinguish two main phases of a technology life cycle: an initial phase of rapid development (early phase), followed by a period of incremental change and maturation (maturity phase). The adoption pattern within each phase mirrors this cycle following a well-documented logistic pattern (Geroski 2000): first, adoption of radically new technology breakthroughs grows exponentially (early phase), lead by early and majority adopters (Rogers 1962); in the second phase, after the diffusion of the technology reaches and surpasses the midpoint of potential adopters, adoption of more mature technology vintages grows at a diminishing rate (maturity phase). The transition between these two phases is marked by a shift in investment growth patterns in the technology.[1]

Theory suggests that during the early phase of the life cycles, new technologies are biased towards skilled workers because early adoption requires higher levels of education and expertise (Tushman and Anderson 1986, Bartel and Lichtenberg 1987, Aghion 2002, and Sanders 2013). During the maturity phase, learning has occurred, technology vintages become more standardized and firms are better able to integrate them, potentially increasing employment and productivity even for lower-skilled workers(Vona and Consoli 2015). For instance, Bartel and Lichtenberg (1987) hypothesizes that education is a necessary condition to adopt a new technology, and once a technology is adopted, firms demand more educated workers. The implication is that early adoption, implementation, and adjustment of the new technology requires highly educated workers. Less educated workers, however, may be in higher demand as the technology matures and becomes more accessible (i.e. in the second phase of the technology life cycle). Aghion (2002) further explains changes in wage inequality within education groups with the diffusion of technologies embodied in new machines, arguing that only a frac-

[1] Consider the case of the Internet and Web-based technologies. The World Wide Web (WWW) began its adoption in high-income countries in the early 1990s, initially limited to academic and research institutions. Early adopters, predominantly skilled professionals, leveraged it for communication and data-sharing. By the late 1990s and early 2000s, widespread adoption among businesses and households enabled e-commerce, cloud-based applications, and digital communication tools. As the technology matured, businesses fully integrated digital tools, and widespread saturation was reached. By the early 2000s, new breakthroughs such as GUI and cloud computing began to emerge, signaling the next life cycle.

tion of workers are in a position to adapt and use the new technology vintages.

In this paper, we empirically test these theoretical predictions. We estimate the short-term impacts of the technology life cycles of digital (Information and Communication Technologies (ICT), Software and Database (SDB)) and automation technologies (Robots) between 1995–2017 on European regional labor markets. Specifically, we examine the impacts of each life cycle phase (early and maturity) on employment and wages, exploring whether the effects differ across technological breakthroughs within each technology category.

We start by identifying technology life cycles from 1995 to 2017, based on major technological developments and investment growth in digital (ICT and SDB) and automation (robot) technologies in the EU. We identify major technological breakthroughs using the technical literature, and determine their life cycle phases based on technology investment growth rates. Since direct firm adoption data is unavailable, we use growth rates of aggregate investment as a proxy to identify periods of rapid adoption expansion (early phase) versus slower, incremental adoption growth (maturity phase) within each technology's life cycle. We identify three technology 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–). Additionally, we identify two technology life cycles reflecting the radical change in robot technologies with the introduction of AI: Robotics (1995–2013) and Intelligent Robots (2013–).

We assess the impact of these digital and automation technologies on European regional labor market outcomes for each technological breakthrough and during their technology life cycle phases. Specifically, we estimate the influence of regional exposure to these technologies on the employment-to-population ratio and average wage. Employment impacts provide evidence on whether higher technological penetration displaces, reinstates, or has no effect on regional employment. Combined with wage impacts, we infer the types of employment that are displaced or created (high- or low-paid), or whether there is a substitution between high- and low-paid workers.[2]

To determine the effects of regional exposure to each technology, we use a shift-share instrumental variable (IV) approach, drawing on prior research (Chiacchio et al. 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, Dauth et al. 2021, Jestl 2024). We adapt the approach to account for technology life cycles. We instrument EU regional exposure with investment in these technologies during the same cycle phase in the US, addressing potential endogeneity

[2]It is worth noting that using data on the type of occupations as an outcome variable would have been preferable. However, our analysis is constrained by the lack of consistent occupational data at the regional level for the period under study and across the entire Europe. We develop an interpretative framework in Section 5 to systematically infer skill-bias from the combined effects on the employment-to-population ratio and the average wage.

concerns.

To maximize data availability, we study these impacts on regional employment rates and the average wage for a sample of 158 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.

Our results support the theory that labor market impacts of digital and automation technologies differ between the early and maturity adoption phases. However, based on wage impacts, we find limited support for the theory that during the first phase, when the technology is first deployed, the early adopters are expected to be more educated and skilled. We observe this pattern for investment in intangible digital technologies such as software and databases, but not for tangible technologies such as ICT and robots. For robots, we observe an increase in the employment-to-population ratio during the early phase, with no skill bias. For ICT, we observe the reinstatement of low-skilled jobs in the early phase, and a displacement of low-skilled workers consistently during the second phase of technology maturity.

Second, in addition to earlier findings that robots and ICT have different impacts on the labor markets, we also find that these impacts differ among different breakthroughs of these digital and automation technologies. Most of the impacts of digital technologies observed between 1995 and 2017 are largely attributable to the first technology breakthrough observed in our data, the popularization of user-friendly computers through Web 1.0 (1995-2004).

Third, during this first technology life cycle, ICT and SDB have opposite effects on regional labor markets, with the former reinstating and the latter displacing low-skilled workers. This result is driven by the early phase of the cycle, in which earlier vintages of the technology are adopted by early and majority adopters. In the regions in which the adoption of ICT and SBD complement each other (regions with similar penetration rate for both ICT and SDB), the two effects cancel out and the overall effect on the labor market is nearly zero. In regions in which ICT adoption dominates, early adopters of Web 1.0 technologies experience an increase in productivity and sales which increases labor demand. In regions in which SDB adoption dominates, low-skilled workers are replaced by fewer high-skilled workers (as predicted by extant theories).

Fourth, while industrial robots are adopted mainly in manufacturing, their (positive) effect on employment within the same region occurs only in services within the same region. We find no impact on the industry employment rate. ICT and SDB, adopted in both industry and services, also exert their main (positive and negative) impact on services. Overall, the main changes in employment and wages seem to be driven by changes in the local demand for services.

This paper contributes to the extensive literature on the impact of digital and 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, ICT, 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.

In particular, we contribute to the relatively thin literature on the role of technology life cycles in influencing the impact of technologies on labor demand (Hirsch 1965, Tushman and Anderson 1986, Audretsch 1987, Xiang 2005, Bartel and Lichtenberg 1987, Aghion 2002, Sanders 2013, Vona and Consoli 2015). For instance, Hirsch 1965 shows that in the electronics industry, science and engineering skills are more relevant in the early stages of technology development, and become progressively less relevant. While the opposite is true for unskilled labor. Management sits in the middle, being most relevant in the growth phase. Audretsch 1987 shows that during the first phase of the life cycle, industries are more skill-intensive. Whereas in the second phase, they rely less on skills and more on capital. Xiang 2005 finds that the production of new goods employs a higher share of skilled workers, making the case that technology is skill-biased.

Our work makes two main contributions to this literature. First, we focus on the adoption side of the technology life cycle, rather than on the product life cycle. This distinction is important because while it is high skilled workers who develop new technologies, from the literature we know that adoption may have varying distributional effects, for instance in favor of high skilled workers (Autor et al. 1998, Autor et al. 2003) or workers performing tasks that are less likely to be codified (Acemoglu and Autor 2011, Acemoglu and Restrepo 2019). This allows for testing specifically the prediction that during the early phase of the life cycles, the technology is biased towards skilled workers (Tushman and Anderson 1986, Bartel and Lichtenberg 1987, Aghion 2002, and Vona and Consoli 2015). That is likely to happen in a scenario in which early adopters of breakthrough technologies, typically the most productive and advanced firms, are also more likely to replace unskilled or routine workers (Autor et al. 2020). However, these early highly productive adopters may also be the ones who benefit most from the technological breakthrough, become more productive, and can reduce production costs and increase final demand (Vivarelli 1995). We can also think of a second scenario in which early adopters hoard workers while they integrate the new technology (Domini et al. 2021).[3] In the second stage of the life cycle, instead, the technology becomes mature and standardized, firms integrate it efficiently, and task routinization is codified, leading to worker replacement.[4] We find that ICT follows the second scenario, SDB the first, while the impact of robots on labor markets in the first phase is not skill biased.

Second, we contribute to explaining the difference between long- and short-run effects of digital and automation technologies on labor markets. In the long run, digital and automation technologies trigger productivity gains (Aghion et al. 2022), demand growth (Vivarelli 1995), and the emergence of new tasks and occupations (Autor et al. 2024), offsetting the displacement of workers responsible for the automated tasks (Simon 1960). As a result, total employment does not change, although its composition does (Autor and Salomons 2018). 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 find that small or non-significant effects in the long run, across different technology life cycles, hide larger short-term effects on employment and its composition, which are likely experienced by workers.

The paper is structured as follows. Section 2 describes the variables and the databases used for our analysis. Section 3 identifies the primary innovation breakthroughs for robots, ICT, and SDB and defines their respective life cycles. 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 them in relation to the extant theory. Section 6 provides concluding remarks.

[3] This is, for example, 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).

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

2 Data

2.1 Sample

We analyze the impact of technology exposure on labor market outcomes across 158 NUTS-2 regions from 12 European countries over the period 1995 to 2017. The 12 countries included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, and Sweden.[5]

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).[6]

We use the employment-to-population ratio as our main employment outcome, defined as the share of employed individuals aged 15 to 64 relative to the total population in the same age group.[7]

For wages, we use the average annual wage compensation per worker, expressed in thousands of euros (2015 values), computed by dividing total employee compensation by the level of total 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 (CT): "specific tools, systems, computer programs, etc., used to transfer information among project stakeholders" (ISO 24765:2017);

[5]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.

[6]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 provides data on population, employment (persons and hours worked), wages, labor costs, gross 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.

[7]We acknowledge that the ratio suffers from the limitation that the denominator may grow more than the numerator in regions with an 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 older. If regions that are aging faster also have an incentive to adopt digital technologies, we expect to see a negative relation between technology adoption and the employment-to-population ratio. We will take this into account when interpreting the results.

3. Information Technology (IT): "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).

We consider computer software (4a) and databases (4b) as a single category, labeled software and databases (SDB). This decision is motivated by two main considerations. First, the EU-KLEMS data we use (discussed further below) do not clearly distinguish between software and databases.[8] Second, these two technologies are highly complementary, making it analytically meaningful to group them. Based on the same rationale, we combine IT and CT into information and communication technology (ICT).

To compute a measure of regional exposure to robots, 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 of the data). Robots are present in three out of six sectors: Industry (B-E), Construction (F), and Non-Market Services (O-U).[9] Since approximately 30% of robots in IFR are not assigned to a sector, we proportionally reallocated them to sectors based on observed sectoral robot shares.[10] Additionally, for countries where the number of robots is not available at the sectoral level for early years (such as the US), we estimate their number by distributing the total number of robots weighted by the average sectoral share using years with available data.[11]

To compute a measure of regional exposure to other digital technologies, we use ICT and SDB data from the EU-KLEMS database (Release 2021). We use data on the capital stock (in

[8]This comes from the fact that it retrieves data from the national statistical offices which follow the Systema of National Accounts (SNA) 2008 in which software and databases are treated as a single category.

[9]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 only have access to 1-digit industry-level data in the ARDECO database, the conversion between Rev 2 and Rev 3.1 introduces marginal differences. Tables A.1 and A.2 provide more details on the harmonization.

[10]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.

[11]For instance, suppose that for a specific country, sectoral robot stock data are missing between 1995–2000. 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.

2015 volumes), derived from national accounts.[12,13] For Denmark and Sweden, we converted EU-KLEMS 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.[14] We do this to absorb the effect associated with 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.[15] This control captures the adverse effects of international competition on local labor markets (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).To construct our instrument (described in Section 4), we normalize the technology stock using sectoral employment data from 1980, sourced from the OECD Annual Labor Force Statistics (ALFS).[16]

3 Technological Breakthroughs and their Life Cycles

Innovations tend to cluster temporally around major breakthroughs, promoting a series of incremental innovations that lead to the next major breakthrough once the technology reaches the maturity stage (Silverberg and Verspagen 2003).

In this section, we qualitatively identify the primary innovation breakthroughs in robots and digital technologies (ICT and SDB) since 1990 by combining insights from the innovation and engineering literature. We then analyze the diffusion patterns of these breakthroughs

[12]Investment would have been a better measure, due to the small differences in accounting for depreciation across national statistical offices. However, due to the different compliance rules across countries, robot flows (robot installations per year) are tracked differently Jurkat et al. (2022), which does not allow for building an investment measure for robots. We therefore use stock for all technologies

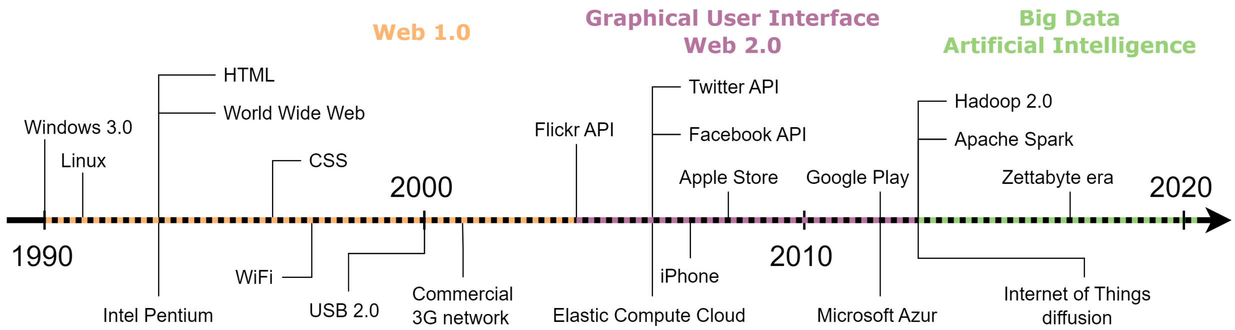
[13]For Ireland, where sectoral stock data are unavailable for ICT/SDB, we allocate country-level technology stocks across sectors based on each sector's share in gross fixed capital formation.

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

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

[16]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 (1993 to 2004), Graphical User Interface and Web 2.0 (2004 to 2013), and Big Data and Artificial Intelligence (from 2013).

across Europe over time, examining investment trends in these three technologies. Specifically, we we distinguish between phases of accelerated (early phase) and decelerated (maturity phase) investment following each breakthrough. Following the well-known logistic diffusion curve (Geroski 2000), we interpret investment accelerations as indicative of early adoption of the new technology, and investment decelerations as signaling later adoption of the technology in a more mature stage.

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 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 F.

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. Software advances (e.g. Windows 3.0) enabled wider ICT diffusion to end-users, though database investments remained relatively low during this phase.

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. Earlier infrastructure developments (e.g., the Internet and mobile communication) enabled the proliferation of user-friendly devices like 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.

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). Improved networking and sensor technologies also supported the rise and the diffusion of the Internet of Things (IoT).[17]

3.2 Breakthroughs in Robots: From Robotics to Intelligent Robots

Robotics. The development of robotics in the 1990s was 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

[17]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.

during the 1990s—such as the Internet, the WWW, and wireless standards—further expanded robots' control capabilities and mobility, enabling the development of mobile robots (Grau et al. 2017). This expansion impacted the automobile industry and, crucially, began to diffuse to other manufacturing industries (Hägele et al. 2016, Gasparetto et al. 2019).

While robots improved over the years, there was no radical change in the technology until 2010, but rather a continuation of the technological patterns observed in the early 1990s. The build up and advancement of Industry 4.0 technologies in the first decade of the 2000s marked the advent of a new era in robotics.

Intelligent Robots. The development of AI technologies in the middle of the 2010s, combined with the emergence of the IoT and sophisticated sensors, paved the way for intelligent computing systems. More sophisticated sensors and wireless communication technologies allow for full 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, leading to the emergence of 'intelligent robots' (Müller 2022).

3.3 Technology Life Cycles in Automation Technologies

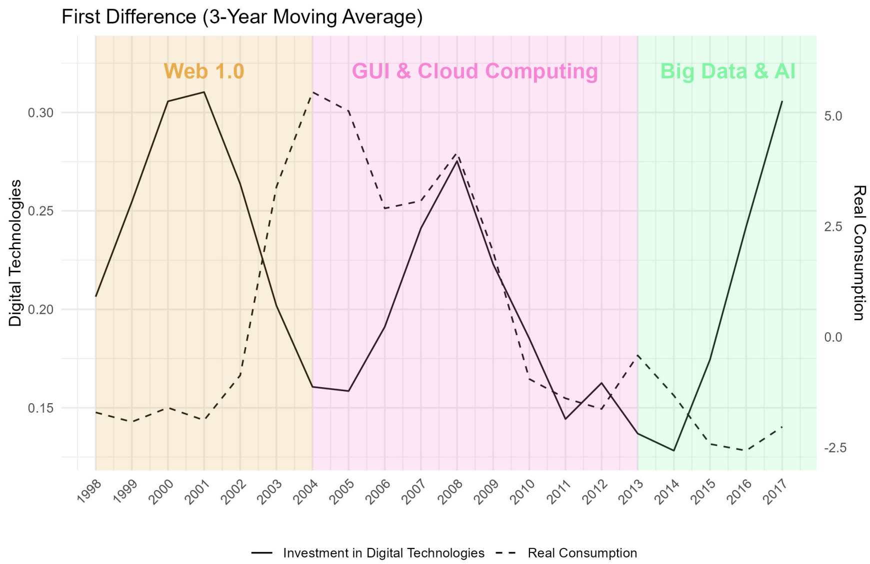
If the breakthroughs identified qualitatively represent major technological developments of ICT/SDB and robots, we should observe an increase in the adoption of these technologies until the rate of adoption has reached its midpoint, followed by a decrease thereafter (Geroski 2000). To check for this, we examine investment in robots and digital technologies since 1990 in Europe. Specifically, we assess whether investment accelerates following a breakthrough (indicating early adoption) and decelerates as the technology matures, potentially leading to the next breakthrough.

We aggregate investment stock in these technologies (per thousand workers in 1980 at constant prices) across all European countries.[18] As expected, investment in digital technologies and robots has increased annually since 1990 (see Figure D.1 in the appendix).

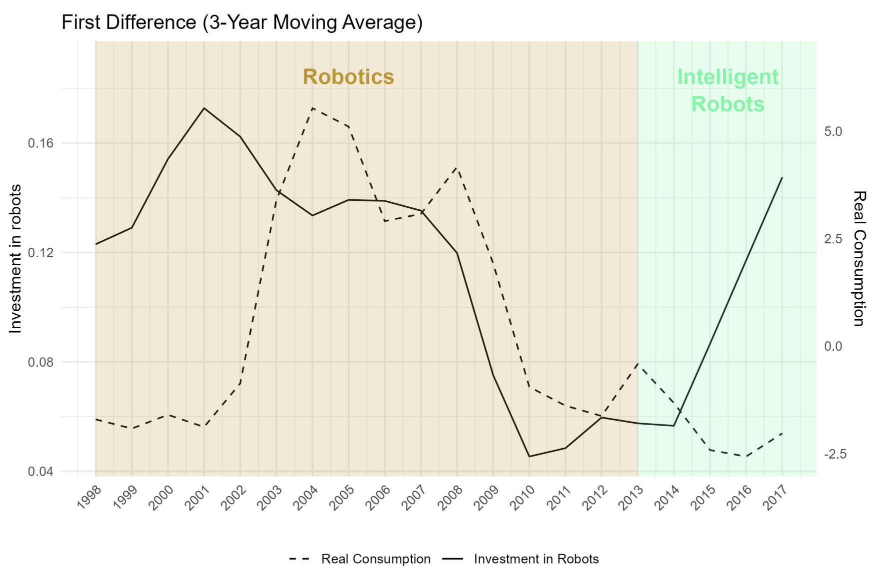
To assess the rate of increase, in Figure 2, we calculate the first difference in the time series after applying a 3-year moving average to smooth short-term fluctuations.

[18]The technology stocks from EU-KLEMS are calculated in volume terms and are not directly additive. Therefore, we used the EU-KLEMS methodology to generate aggregates (Bontadini et al. 2021). This is, 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 Robot in Europe (First Difference)



(a) Digital Technologies



(b) Robots

Notes: Panel 2a 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). Panel 2b 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.

The left y-axis depicts the change in investment in digital technologies (Panel 2a) and robots (Panel 2b). To distinguish investments driven by the technology cycle from the business cycles, we plot the trends in final demand (real household consumption) on the right y-axis of each panel as a proxy for the latter.[19]

The investment patterns in digital technologies (robots) from 1995 to 2017 exhibit three (two) distinct phases of acceleration and deceleration. For both technologies, their investment cycles show an acceleration after the breakthrough identified in the literature (increase in adoption rates), followed by a deceleration (decrease in adoption rates). Following the literature (Rogers 1962), we refer to the initial surge in investment during the early stages of the technological breakthrough as the *early* phase of the technology life cycle, driven by early and majority adopters, experimenting with the initial vintages of the technology. We refer to the subsequent slowdown in investment as the *maturity* phase when the remaining late adopters integrate these technologies.

More in detail, let us consider, for instance, digital technologies: ICT. The Web 1.0 breakthrough emerged in the early 1990s, and gave way to an acceleration in ICT investment (first phase) until around 2001, followed by a decline in the investment rate of change up to around 2004/5 (second phase). Ariund that time, the second breakthrough in digital technologies emerged, giving way to the second technology life cycle observed during our period of analysis: GUI and cloud computing. Investment rates again rose until 2008 (first phase), and then declined before the next breakthrough (big data and AI) in 2014 (second phase). The third technology life cycle began around 2014, and the first phase of increased investment and adoption is still ongoing through 2017.

Notably, the investment cycles for digital technologies and robots do not align with business cycles, with the exception of the second phase of the GUI & Cloud Computing technology life cycle. To address this overlap, we control for the domestic demand in our empirical strategy.

Investment in robots (Figure 2b) also confirms the distinction between two breakthroughs and their life cycles: robotics (1995–2013) and intelligent robots (2014 onward). During the first cycle, investment accelerates (first phase of early and majority adopters) up to 2001, when the technology is adopted by half of the potential adopters. From then till 2013 adoption rate decreased, led by the diffusion through late adopters in Europe. This lasts until the breakthrough combining robots with AI and the development of intelligent robots. This second robot technology life cycle started in 2013, showing an increase in adoption rates through the period observed in our data (2017).

[19]Household consumption is the largest component of aggregate demand, and tends to be less volatile than investment, helping to identify underlying trends in the business cycle.

Table 1: Phases of the Technology Life Cycles

Cycle	Phase	Period
Digital Technologies		
Web 1.0	↗	1995-2001
	↘	2001-2004
GUI & Cloud Computing	↗	2004-2009
	↘	2009-2013
Big Data - AI	↗	2013-2017
Robots		
Robotics	↗	1995-2002
	↘	2002-2013
Intelligent Robots	↗	2013-2017

Notes: This table summarizes the years of each phase in the technology life cycles of digital technologies and robots. A ↗ indicates the first phase of rapid diffusion of early vintages of the technology, whereas a ↘ indicates the last phase of slower diffusion of later vintages of the technology.

Table 1 summarizes the technology life cycle phases.

Robustness Checks. To validate our results, we also regressed the investment time series for robots and digital technologies against a linear time trend and real consumption per thousand workers in 1980 aggregated at the European level.[20] Figure D.1 in the appendix shows the results. 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. The figure shows that the evolution of the first difference series, and consequently, the phases of investment, are very close to those in Figure 2a. Hence, we can be confident that our approach captures periods of rapid change (either increase or decrease) in technology investment.

The investment patterns in robots and digital technologies in Europe follow the patterns of the technology lifecycle, characterized by two phases: a first phase of increasing rates of adoption (investment) following a breakthrough, and a second phase of decreasing rates of adoption (investment) as the technology matures and before the next breakthrough. In what follows, we study if the impact of digital and robot technology differs for different breakthroughs and different phases of the technology life cycle within each of them.

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

4 Empirical Specification

We estimate the impact of investment in robots, ICT, and SDB on regional labor markets in Europe, across different phases of their technology life cycles. We calculate technology exposure as the change in the technology stockper worker using a shift-share measure across different phases of each technology cycle of robots, ICT, and SDB. We estimate our baseline model for labor market adjustments associated with technology exposure during each phases. Finally, to address identification issues, we implement an IV strategy that uses US technology investment as an instrument for technology investment in Europe.

4.1 Shift-share Technology Exposure in Technological Investment Phases

Because available data on robots, ICT, and SDB stocks are at the national level, we measure the 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, Jestl 2024). 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 corresponding to 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 then 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

[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.

exposure is defined as the sum of the exposures calculated for each phase:

$$(Exposure_r^K)_{1995}^{2017} = \underbrace{\sum_{i \in I} l_{ri,1980} \left(Tech^K_{c(r)i,2017} - Tech^K_{c(r)i,t+h'} \right)}_{\equiv Exposure^K_{r,2}} + \underbrace{\sum_{i \in I} l_{ri,1980} \left(Tech^K_{c(r)i,t+h'} - Tech^K_{c(r)i,1995} \right)}_{\equiv Exposure^K_{r,1}},$$

where 1 refers to the technology investment phase between 1995 and $t+h'$ and 2 to the technology investment phase between $t+h'$ and 2017. This split in exposure can be generalized to any number of phases as follows:

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

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 each phase τ. The outcome variable, $y_{r,\tau}$, represents the change in the relevant labor market indicator for region r specifically during 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 3.3.

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 their life cycles, we estimate the following specification:

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

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

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 average wage are calculated as log changes, allowing the coefficients to be interpreted as approximate 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 institutions and regulations (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 productivity 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, measurement practices for tangible and intangible capital (such as ICT and software) vary across countries and over time and are only partially harmonized in EU-KLEMS, which means that the estimates derived from Equation (3) by OLS may be downward biased due to measurement error. The overall direction of the OLS bias, given simultaneity, omitted variables, and measurement errors, depends on the prevailing source of endogeneity for different technologies.

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

Following the instrumental variable strategy employed by Acemoglu and Restrepo (2020), and building on recent studies that examine the effects of automation on European regional labor markets–such as Antón et al. (2022) and Jestl (2024)–we use technological investment data from the United States, which is a large economy experiencing sharp automation changes, as an instrument for European technology adoption.[23]

We construct the exposure of European regions during phase τ by measuring the change in automation technologies in the U.S. (exogenous shift) over the same phase, while holding constant the initial employment shares from European regions (share). The instrument for technology K in region r during phase τ 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 years t and $t+h$ correspond to the start and end of the cycle phase τ, respectively.

By considering changes in technology in the US, we capture shifts in technology that influence its diffusion in Europe, although plausibly uncorrelated with regional labor markets in Europe. We allocate investment proportionally according to the exposure of each region in 1980, based on its sectoral specialization measured with employment.

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

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

where $Exposure_{r,\tau}^{K}$ is the endogenous exposure to technology K in the European region r for the phase τ, as defined in Equation (1), $Exposure_{r,\tau}^{K,US}$ is the instrument for the phase, as outlined in Equation (4), and ε_r is the error term.

5 Labor Market Impacts

In this section, we examine the results of our estimations of the impacts of exposure to robots, ICT, and SDB on the employment-to-population ratio and average wage during different phases of these technologies' life cycles. We assess the differences between the effects over the long run (i.e., 1995–2017), for each technological life cycle defined in Sections 3.1 and 3.2, and for

[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 US, employment trends in EU countries are more closely correlated because of shared global value chains and human capital flows. US investments in automation are less likely to impact European labor markets directly.

both phases of each technology life cycle identified in Section 3.3: the early adoption phase (associate with early and majority adopters), and the maturity adoption phase (associated with late adopters). We also disaggregate the results at the sectoral level to identify which industries drive the results.

5.1 Analytical Framework

Table 2 outlines how we assess the net regional employment effect based on the estimated impact of technology exposure on the employment-to-population ratio and the average wage. This matrix provides an interpretative framework for distinguishing between displacement, reinstatement, and skill substitution effects.

Table 2: Interpretation of the Net Employment Effects based on Estimates at the Regional Level

	Emp-to-pop. ratio		
Average Wage	$+$	0	$-$
$+$	Reinstate H	Substitute L with H	Displace L
0	Reinstate	No Effect	Displace
$-$	Reinstate L	Substitute H with L	Displace H

Notes: This table provides a framework to interpret the net effect of technologies on employment based on the estimates obtained at the regional level. H refers to high-skill workers and L to low-skilled workers.

A positive employment-to-population ratio effect (first column) suggests a net creation of employment (reinstatement). This may may result from the emergence of new tasks, occupations, or industries, or from a higher labor demand in existing ones, increasing the demand for human workers in the region. Workers may be sought within the industry adopting the technology (for instance, due to an increase in sales) or in other industries in the same region (for instance, creating demand for new services outsourced locally by adopting industries). We then infer the type of employment that is created based on the sign of the wage estimate. When the regional average wage increases (decreases), this suggests that the employment creation is biased toward high-skilled (low-skilled) workers. When the wage estimate is not significantly different from zero, we interpret this as an increase in employment of both types of labor in similar shares.[24]

[24]It is important to note that while differentiating the outcome variable by worker type would provide valuable insights, the lack of consistent data on occupations and education at the regional level prior to 2010 prevents us from doing so. As a result, we use a combination of the employment-to-population ratio and average wage as a proxy for this outcome.

Conversely, when the employment effect is negative (third column), this suggests a net destruction of employment (displacement). This may be because of the substitution of workers by the technology, with an insufficient increase in sales or in the demand for ancillary industries from the same region to compensate. Again, the technology may replace workers within the firms/industry adopting the technology, or by reducing the demand for goods or services procured from the same region. Similarly, we can infer the type of workers who are displaced from the wage impact. When the regional average wage increases (decreases), this suggests that displacement is biased toward low-skilled (high-skilled) workers. When the wage estimate is not significantly different from zero, we interpret this as a skill-neutral displacement of workers.

Lastly, the skill-substitution patterns (second column) appear when the regional employment-to-population ratio coefficient is not significant, but the average wage coefficient is. When the wage coefficient is positive (negative), this suggests that the employment of high-skilled (low-skilled) workers has increased at the expense of low-skilled (high-skilled) workers—indicating a substitution of one type of worker for another. When both coefficients are not significant, we interpret this as a null effect on employment. This may occur when the technology either complements or substitutes workers, and the increase in sales or in the demand for ancillary industries located in the region compensates for the labor displacement.

Table C.22 in Appendix C summarizes the employment effects of each technology based on the interpretation provided in Table 2.

Tables C.13 to C.14 present the IV results for the labor market impact of robots and digital technologies—ICT and SDB combined (Table C.14) and separately (Table C.15).[25] Each column corresponds to a different time period. The first column in each table shows the long-run effect (1995-–2017) of a one-standard-deviation increase in regional exposure to each technology on labor market outcomes. Panel A presents estimates for the employment-to-population ratio, while Panel B shows the average wage. The remaining columns in Tables C.13, C.14, and C.15 provide estimates for both phases of each technology life cycle: the *early phase*, associated with *early and majority adopters* (when investment accelerates), and the *maturity phase*,assocaited with *late adopters* (when investment slows).

5.2 Long-Run Impacts (1995–2017)

We find that the long-run labor market impacts of robots and digital technologies—across the different technology life cycles (1995–2017)—differ among the three technologies. Robots have a positive impact on the employment rate over the entire period with a 1-STD increase in

[25]Tables C.1 to C.3 show the OLS results, while Tables C.10 to C.12 display the first stage results.

exposure leading to a 0.11 pp. yearly increase in the employment-to-population ratio (Table C.13, Panel A, Column (1)). This corresponds to a 2.42 pp. increase over the 23 years. The effect on the regional average wages of such an increase in the employment rate is null (Table C.13, Panel B, Column (1)). We interpret this result as indicating that robots have an effect that is neutral toward either low- or high-skilled workers. However, this aggregate result could mask compositional changes, such as displacement in adopting sectors offset by creation in others, or shifts of low-skilled workers to less exposed service industries. We can only observe the aggregate net effect.

Tables C.16 and C.17 show the regional labor market impact of exposure to robots by sector, respectively for the employment rate and the average wage. These results (Column (1)) suggest that the positive skill-neutral impact of robots on the regional labor market is driven by the creation of employment in services, without significantly altering the average wage. This implies that higher exposure of EU regions to robots did not have a net impact on employment in the sectors that adopt the technology—namely, industry. The positive effect is due to job creation in ancillary (non-tradable) services.

We find no effect of digital technologies (ICT and SDB combined) on employment over the entire period (1995–2017), as shown in Table C.14, Panel A, Column (1). However, Table C.15 suggests that this aggregate result is due to the opposite effect of ICT and SDB on employment and wages. A 1-STD increase in exposure to ICT (SDB) leads to a 0.05 (-0.06) pp. *yearly* increase (decrease) in the employment-to-population ratio (Table C.15, Panel A, Column (1)), i.e., 1.1 (1.32) pp. increase (decrease) over the entire period. Since, on average, regions are highly exposed to both ICT and SDB (Figure E.1), the two effects offset each other. However, the figure also shows that several regions are mostly exposed to one of the two technologies. These regions have experienced an asymmetric employment response to exposure to digital technologies depending on the dominant technology.

We find an opposite impact of ICT and SDB exposure also on the average regional wage in the long run (1995–2017). Regions with a 1-STD higher exposure to ICT (SDB) have seen a yearly decrease (increase) in the average yearly regional wage by -0.23 (0.26) percent (Table C.14, panel B, Column (1)). Consequently, for regions with balanced exposure to both, the net wage effect is small. For regions predominantly exposed to one type, the wage effects are more pronounced. Again, we cannot rule out various compensations in the distribution of jobs over this long time period. However, regions exposed more to ICT than to SDB have seen a reinstatement of low-skilled workers, with wages declining both in industry and services (Table C.21, Column (1)). Regions exposed more to SDB than to ICT, conversely, have seen a displacement of low-skilled workers, both in industry and services. This may be due to the canonical skill bias of the technology, which replaces mainly low-skilled routine tasks.

5.3 The Role of Technology Life Cycles: Short-Run Impacts

As suggested by the literature, long-run impacts of technological investments on the labor market may level off short-run impacts of each technology breakthrough, and/or impacts taking place during different phases of their life cycle. We explore these short-run dynamics in this section, for robots and digital technologies, using the same interpretative framework presented in Table 2.

Table C.13 reports results for the two life cycles of robot technology: robotics (Column (2)) and intelligent robots (Column (5)). The robotics cycle is further divided into the *early* phase (Column (3)), when early and majority adopters are more likely to invest, and the *maturity* phase (Column (4)), when late adopters are more likely to invest. For the recent breakthrough in intelligent robotics, we observe only the beginning of the first phase up to 2017.

We find a positive impact of robots on employment for both breakthroughs, though considerably larger for the first one. During the robotics cycle (1995–2013), a 1-STD increase in robot exposure over this period leads to a 2.16 percentage point increase in the employment-to-population ratio (0.12 pp per year). Most of this positive effect occurs during the *early* phase, as indicated by the 0.22 estimate in column (3) of Table C.13 (panel A). During the intelligent robots cycle (2013–2017), for which we only observe the early phase, we also find a positive impact on employment, though of a lower magnitude (0.07 pp per year). However, it is important to note that the early phase of intelligent robots may not yet be complete, as our analysis is limited by data availability to 2017.

We then examine the estimates for the average wage in Panel B of Table C.13 to determine whether the employment impact was biased toward a specific labor type. For the robotics cycle (1995–2013), we find a negative but statistically insignificant coefficient (Panel B, Column (2)). Similarly, the early phase of this cycle exhibits a negative coefficient but with large standard errors. Overall, this suggests that the positive employment effect observed during this cycle is not skewed toward high-skill workers and may instead reflect an increase in low-skill employment. However, the large standard errors observed in this column indicate heterogeneity across regions.

For the early phase of the intelligent robots cycle (2013–2017), we find a positive and significant coefficient, suggesting that the employment gains from this technological breakthrough primarily benefit high-skill workers rather than low-skill ones. As these new robots integrate AI and gain mobility, they can substitute low-skilled workers in tasks increasingly susceptible to automation and routinization via intelligent control.

Tables C.16 and C.17 further confirm that the positive employment effect observed during the first phase of the robotics life cycle (Column (3) for the first phase, or (2) for the overall first cycle) is not driven by the sectors with the highest adoption shares of robots (i.e., industry).

Instead, it reflects increased demand in related services, as employment in the service sector grows while the average wage remains stable, suggesting a neutral effect on skill composition.

For digital technologies (ICT and SDB combined), we find that despite the null effect over the long run, there is a significant impact on the employment rate, primarily concentrated during the Web 1.0 cycle (1995–2004) (Table C.14, Panel A, Column (2)). During this first technology life cycle, a 1-STD increase in exposure to digital technologies leads to yearly decline of 0.09 percentage points in the employment-to-population ratio (totaling -0.81pp over the 9-year cycle). This negative impact is concentrated during the maturity phase of the Web 1.0 cycle (2001–2004) (Column (4)), whereas the early phase (1995–2001) had a positive effect on employment (Column (3)).

Examining Panel B of Table C.14 (Columns (2), (5), and (8)), we find that digital technologies re associated with gains for high-skilled workers during the Web 1.0 cycle (1995–2004). A 1-STD increase in exposure to digital technologies during this period leads to a yearly increase of 0.24% in the average wage (totaling 2.16% over the cycle), suggesting that low-skilled workers are, on average, displaced. When analyzing the two phases of this cycle separately, we see that this skill-biased impact is primarily driven by the maturity phase (Column (4)), where low-skilled workers appear to be replaced as ICT and SDB-enabled automation takes over their tasks.

For the subsequent breakthroughs—the Graphical User Interface & Cloud (2004–2013) and Big Data & AI (2013–2017)—we do not find any significant impact of digital technologies on the employment-to-population ratio. However, during the early phase of both cycles (Panel B, Columns (6) and (8)), we observe positive estimates for the average wage. This suggests that while the net employment effect remained neutral, there were gains in the average wage in regions with higher exposure to digital technologies as early adopters embraced these new vintages.

As noted above, in the long run, ICT and SDB investments have opposite effects on employment and wages, which offset one another for regions exposed to both. We now examine how these effects differ across the two phases within each of the three life cycles using the disaggregated results from Table C.15. We again find that most of the impact on employment occurs during the Web 1.0 technology life cycle (1995–2004) (Table C.15, Column (2)). Regions with a 1-STD higher exposure to ICT (SDB) experience a yearly increase (decrease) in the employment rate of 0.22 (-0.29) percentage points. The stronger negative impact of SDB drives the overall negative effect on employment in regions that are exposed to this breakthrough in both ICT and SDB (Table C.14, Panel A, Column (2)).

For both technologies, the employment effects are even stronger when disaggregated by the early and maturity phases of the Web 1.0 life cycle (Table C.15, Columns (3) and (4)). Specifically, ICT positively impacted the employment-to-population ratio during the early phase (0.62 pp. yearly, totaling $+3.72$ pp.) but had a negative effect in the maturity phase (0.71 pp. yearly, totaling, -2.13 pp.). Conversely, SDB had a negative effect in the early phase (0.37 pp. yearly, totaling -2.22 pp.) but a positive impact in the maturity phase (0.38 pp. yearly, totaling $+1.14$ pp.).

During the second technology life cycle, Graphical User Interface (GraphUI) & Cloud Computing (2004–2013), the impact of ICT and SDB penetration on regional employment is substantially smaller, and statistically significant only in the maturity phase (Table C.15, Columns (5) to (7)). Once again, ICT and SDB exhibit opposite effects.

Examining the estimates in Panel B of Table C.15 on average wages provides further insights into which types of labor were most affected during each phase of both the first and second life cycles. The increase in employment driven by ICT during the early phase (of the Web 1.0 life cycle) is primarily associated with an expansion in low-skilled employment. In contrast, the employment decline during the same early phase of the first life cycle due to SDB suggests the substitution of low-skilled workers with high-skilled ones. During the maturity phase, these effects reverse direction, but they are not statistically significant, suggesting that the initial phase dominated by early and majority adopters primarily drives the observed changes in skill composition during the adoption of these ICT and SDB vintages.

We do not find significant impacts on average wages during the second life cycle (GraphUI – Cloud Computing, 2004–2013), indicating that technology adoption in the maturity phase of this cycle did not substantially alter the relative demand for skilled and unskilled workers.

Tables C.20 and C.21 show that, similar to robots, the effects of ICT and SDB on employment accrue mainly in the service sector. The key difference is that while robots are primarily adopted in industry, ICT and SDB are used in both industry and services.

5.4 Implications for the Technology Life Cycle Theory of Employment Impacts

Taken together, our results empirically complement existing theories on how the technology life cycle of digital and automation technologies shapes labor markets in the short run. To summarize, the theory posits that during the *early* phase of the technology cycle, corresponding to *early and majority adopters*, early adopters are expected to hire more educated and skilled workers (Bartel and Lichtenberg 1987, Aghion 2002, Vona and Consoli 2015). Our findings partially support a skill bias during the early stage of a technology's life cycle. We observe this pattern for investment in SDB, but not for ICT and robots.

For robots, we see an increase in the employment-to-population ratio during the early phase of both cycles, with no skill bias. Different from theory predictions, we do not observe an increase in the average compensation. The average wage of regions most exposed to robots remains unaffected in any phase of the first technology life cycle. Early adopters in the first phase of the second cycle show high-skill bias driven by services, not among direct adopters of robots in industry.

For ICT, we observe a net reinstatement of low-skilled jobs in the early phase of Web 1.0, followed by a consistent displacement of low-skilled workers in the maturity phase. The fact that the positive impact on the employment rate for low-skilled workers is primarily observed during the first phase of the technology life cycle suggests that increases in sales and other factors driving labor demand in complementary services are largely concentrated in regions adopting the technology during this early phase (early and majority adopters), rather than in regions that adopt the technology during its maturity phase.

Intangible technologies such as SDB more closely align with theory predictions that during the phase of early and majority adopters (early technology phase), regions most exposed to the technology replace low-wage jobs, inducing an increase in the average wage (e.g., in service sectors such as professional and information services). We observe this pattern especially in the first technology life cycle, Web 1.0. This is reversed in the maturity phase of the technology life cycle when regions experience an increase in the employment ratio biased towards low skilled workers. This likely reflects gains in productivity or other demand-enhancing effects that emerge once the technology becomes standardized and widely adoptedin the maturity phase, creating new jobs in services for lower-skilled workers.

5.5 Validity and Robustness Checks

The empirical findings presented above are based on an instrumental variable (IV) estimation strategy designed to mitigate potential endogeneity concerns. In this section, we assess the validity of our identification strategy and examine the robustness of our results.

First, Tables C.10 to C.12 in the appendix present the first-stage regression results for robots, ICT, and SDB across different phases of the technology life cycle. The estimated coefficients are consistently positive and statistically significant across all specifications, supporting the strength and relevance of the instrument.

Second, given that our IV strategy follows a Bartik-type approach, we implement the validity checks proposed by Goldsmith-Pinkham et al. (2020). Specifically, we decompose the IV estimator into the Rotemberg weights (α_k) and the just-identified estimators (β_k). This decomposition enables a clearer understanding of the influence of each instrument on the overall estimate. If a particular instrument is misspecified, the Rotemberg weights indicate the extent to which this misspecification contributes to biasing the estimator. When α_k is small, any potential bias from the k^{th} instrument has limited impact on the aggregate IV estimate (Goldsmith-Pinkham et al. 2020). This diagnostic thus helps evaluate the stability of the estimator with respect to dominant sources of identifying variation.

In light of this, Tables C.23 to C.25 in the appendix show the summary statistics of the Rotemberg weights, identifying the top five country-industry combinations (i.e., instruments) that account for the largest share.

Regarding robots, Table C.23 shows that the top five country-industry pairs account for 92.25% of the total absolute sum of Rotemberg weights. Unsurprisingly, the variation is primarily driven by the manufacturing sector, which is the primary adopter of industrial robots in the IFR data (Müller 2022). The weight concentration indicates a strong influence of Germany on the estimates, which alone accounts for nearly 64% of the total. We further explore this in Figure C.1, which plots the just-identified estimator (β_K) on the y-axis and their Rotemberg weights (α_k) on the x-axis, representing the weight each cell receives in the Bartik IV estimator. Marker size reflects the absolute magnitude of the weight, and color differentiates between cells with positive (blue) and negative (orange) weights. Figure C.1 indicates that the German manufacturing instrument yields an estimate close to the overall average. However, some heterogeneity exists—especially among instruments with very small weights. To assess whether this concentration biases our results, we conducted an additional robustness check, excluding German regions from the sample. The results, presented in Table C.26, are closely aligned with those in Table C.13, suggesting that the dominance of German instruments does not significantly distort the IV estimates.

Concerning ICT exposure, Table C.24 shows that the five country-industry pairs with the largest Rotemberg weights account for 43.37% of the total absolute weight. Notably, the most recurrent industry across countries is sector G–J, which comprises information and communication-related activities. These sectors are not only major users of ICT technologies but they are also central to their production and innovation, which helps explain their prominent role in driving the instrument's identifying variation. We further explore the distribution of Rotemberg weights and the heterogeneity of the just-identified estimates in Figure C.2, which plots each β_k (the just-identified IV estimate using a single instrument) against its corresponding Rotemberg weight α_k. A small number of instruments receive relatively large weights, and their associated β_k estimates are concentrated around the overall IV estimate (represented by the dashed line in the figure).[26] The presence of influential units underscores the importance of robustness checks. Given the prominent influence of Spanish regions in sectors O–U and

[26]Although some instruments receive negative weights, their corresponding β_k values also tend to cluster around the overall IV estimate, which somewhat mitigates concerns regarding identification.

G–J (as highlighted in Table C.24), we perform a robustness check by excluding these Spanish regions. Table C.27 indicates that the estimates remain closely aligned with those reported in Table C.15, providing further confidence in the robustness of the IV results.

Concerning software and database, Table C.25 shows that the top five industries with the largest Rotemberg weights account for 55.57% of the total sum of absolute weights. These industries include not only key producers of such technologies (J), but we also observe a strong influence from industry K–N, which includes financial services. This is consistent with expectations, as this sector heavily relies on software and databases. As with ICT, the instruments with the largest weights tend to cluster around the overall IV estimated coefficient, as displayed in Figure C.3. Similar to what was observed in the ICT case (although with substantially smaller weights and difference in coefficients), the observed heterogeneity primarily stems from instruments with lower weights.

Lastly, an important concern relates to the pre-trend dynamics in our outcome variables of interest, which serve as additional evidence to support the validity of the instrumental variable strategy. Our instruments—constructed by interacting changes in U.S. technology stock with NUTS-2 industrial employment shares in 1980—rely on the assumption that these historical employment structures are exogenous to subsequent employment dynamics. Yet, if regions more exposed to these technologies due to their 1980s sectoral composition were already experiencing different employment-to-population trends prior to 1995, this would raise concerns about the validity of our identification strategy. In such a case, the instrument might be capturing not only the effect of technology adoption, but also underlying structural changes in employment patterns that predate the observed technological shifts. Therefore, testing for pre-existing differential trends allows us to assess whether the instrument is fully exogenous or instead correlated with prior regional labor market trajectories, which would undermine the causal interpretation of the estimated effects (Acemoglu and Restrepo 2020).

In light of this, Table C.28 reports results for our outcome variables—employment-to-population ratio and average wages—for the period 1983–1989 (prior to our main period of analysis) and for 1995-2001, the first phase of the first cycle.[27] The coefficients for the pre-trend period for robots and ICT are small and mildly significant, while for software and database they are not significant.

The main reason for this is that, due to data limitations, we estimate technology life cycles starting in 1995. However, it is well possible that the first cycle (and its first phase) start well before 1995, as discussed in our technical review in Section 3. This seems to be particularity

[27]Note that data on two control variables—imports and real consumption—are not available for the 1983–1989 period. As a result, these controls were excluded from the regressions reported in Table C.28. This explains why the coefficients in the second column of Table C.28 do not exactly match those in the third column C.15.

the case for robots. As suggested by Figure 2b, 1995-2001 seems to be the end of a long phase that starts before, which would explain the more significant coefficient. As noted in Section 3 a limitation of our analysis is that we cannot perfectly identify the first and last technology life cycles.

6 Conclusion

This paper investigates the impact of labor market exposure to multiple breakthroughs of robots, information and communication technologies, and software and databases across 158 European regions in 12 countries between 1995 and 2017. We identify distinct technology breakthroughs, and examine their correlation with periods of acceleration and deceleration in investment trends. We define phases of rapid investment growth as the *early phase* of the technology adoption life cycle (i.e., corresponding to *early adopters*), while periods of deceleration in investment grwoth represent the *maturity phase*, corresponding to *late adopters*. Our focus is on the labor market impacts of these technologies—specifically, on the employment-to-population ratio and average wage—during the early and maturity phases. To address endogeneity concerns, we use a shift-share IV strategy leveraging U.S. investments as an instrument for European technological investment.

Our analysis yields four main findings. First, we provide partial support for the theory that technology adoption tends to be more high-skilled biased during the early adoption phase. We observe this in the case of intangible digital technologies like software and databases (which tend to displace low-skilled workers or substitute them with high-skilled ones in the early adoption phase), but not for tangible technologies such as ICT (which tended to reinstate low-skilled workers in its early phase) and robots (where the initial robotics cycle showed skill-neutral employment gains in its early phase). Second, the most pronounced labor market impacts of these technologies are confined to the first technology life cycle—Web 1.0 and Robotics, approximately 1995–2004. During this period, robots and digital technologies, respectively, had a significant effect on employment and wages. Third, while ICT and SDB are highly complementary technologies, they have opposing labor market effects. ICT is associated with the reinstatement of low-skilled jobs in its early phase, whereas SDB is associated with the displacement of low-skilled workers. Finally, the labor market effects of robots, ICT, and SDB are predominantly driven by adjustments in the services sector. Even though robots are primarily adopted in industry, their net positive employment impacts are observed primarily in services.

These findings have several policy implications. One main implication of our study is that policies should pay closer attention to the short-term effects of automation, which vary significantly among technologies and across the two phases of their life cycles. Targeted interventions are needed to support workers adversely affected by automation in the short run. Specifically, policies should consider measures to mitigate the negative short-term negative effects on employment seen in the maturity phase of ICT investments and the early phase of SDB investments. Additionally, it is crucial to address the long-term wage decrease associated with ICT adoption, which risks exacerbating regional wage inequality. Labor market institutions, alongside active labor market policies such as retraining and skills development, could play an important role in alleviating these adverse effects, from attracting early adopters which have displacement effects.

Our study has some limitations, suggesting directions for future research. The main limitation is the lack of granular data on the adoption of specific technologies across regions. While our data measure country-specific differences in exposure to technology, our approach assumes uniform adoption of these technologies across regions. Additionally, our analysis cannot differentiate between early and late-adopting firms within a region. This precludes finer-grained heterogeneity in technology diffusion patterns and highlights the need for more comprehensive comparative studies of countries and regions, using comparable firm-level and employee data. Moreover, given the varying impacts on different worker types suggested by our aggregate findings, a task-based approach using detailed employee data could provide more precise insights into whether technology life cycles significantly affect workforce composition and skill demand. Further research should also investigate spatial spillovers and the interaction between technology adoption and labor mobility across regions.

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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 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.1: 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 158 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.

C Regressions

C.1 OLS Regressions

Impact of Robots and Digital Technologies in Regional Labor Markets – OLS

Table C.1: Impact of Robots during Robot Phases

	OLS Reg. - Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.08^{***}	0.09^{***}	0.14^{***}	0.19^{***}	-0.12^{***}
	(0.02)	(0.02)	(0.04)	(0.03)	(0.03)
R^2	0.35	0.36	0.33	0.43	0.46
Num. obs.	158	158	158	158	158
F statistic	16.68	17.07	15.02	23.03	26.08
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	-0.18^{**}	-0.32^{***}	-0.77^{***}	-0.17^{***}	0.51^{***}
	(0.07)	(0.07)	(0.12)	(0.04)	(0.06)
R^2	0.24	0.38	0.31	0.58	0.38
Num. obs.	158	158	158	158	158
F statistic	9.84	18.70	13.97	41.40	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 change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.2: Impact of ICT and SDB during Digital Technology Phases

	OLS Reg. - Dep. var.: Annualized Δ in Outcome Variable							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*								
ICT Exposure	0.02^{*}	0.01	0.01	-0.15^{***}	-0.10^{***}	0.09^{***}	-0.27^{***}	-0.02
	(0.01)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.05)	(0.03)
SDB Exposure	-0.01	-0.01	0.04	-0.08^{*}	-0.04	0.01	-0.16^{***}	-0.12^{***}
	(0.02)	(0.03)	(0.04)	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)
R^2	0.35	0.49	0.22	0.18	0.57	0.29	0.85	0.46
Num. obs.	158	158	158	158	158	158	158	158
F statistic	16.68	28.69	8.80	6.87	40.52	12.20	167.24	26.08
[B] Δ *Average wage (in log)* $\times$ *100*								
ICT Exposure	0.21^{***}	0.30^{***}	0.30^{***}	0.72^{***}	0.06	0.22^{***}	0.32^{**}	-0.18^{***}
	(0.05)	(0.09)	(0.11)	(0.12)	(0.05)	(0.06)	(0.14)	(0.06)
SDB Exposure	0.06	-0.21^{*}	-0.23^{*}	-0.04	0.11^{**}	0.12^{**}	-0.23^{**}	0.28^{***}
	(0.07)	(0.11)	(0.12)	(0.10)	(0.05)	(0.06)	(0.10)	(0.07)
R^2	0.24	0.39	0.23	0.51	0.56	0.37	0.70	0.38
Num. obs.	158	158	158	158	158	158	158	158
F statistic	9.84	19.76	8.95	31.30	39.26	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 change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.3: Impact of Digital Technologies

	OLS Reg. - Dep. var.: Annualized Δ in Outcome Variable							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*								
DIG Exposure	0.05^{***}	0.07^{**}	0.09^{**}	-0.11^{**}	-0.11^{***}	0.11^{***}	-0.29^{***}	-0.13^{***}
	(0.01)	(0.03)	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.39	0.50	0.24	0.14	0.55	0.30	0.82	0.48
Num. obs.	158	158	158	158	158	158	158	158
F statistic	24.59	38.89	12.12	6.38	47.32	16.04	169.30	35.02
[B] Δ *Average wage (in log)* $\times$ *100*								
DIG Exposure	-0.01	-0.29^{***}	-0.31^{**}	0.13	0.15^{***}	0.09	0.18^{**}	0.06
	(0.07)	(0.11)	(0.13)	(0.13)	(0.04)	(0.07)	(0.09)	(0.06)
R^2	0.12	0.37	0.21	0.39	0.57	0.30	0.69	0.32
Num. obs.	158	158	158	158	158	158	158	158
F statistic	5.23	22.82	10.07	24.01	50.89	16.48	85.52	17.99

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 change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Impact of Robots and Digital Technologies in Regional Labor Markets by Sector – OLS

Table C.4: Impact of Robots on Sectoral Employment Rate. Robot Phases

	OLS Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] *Agriculture*					
ROB Exposure	0.02^{***}	0.03^{***}	0.03^{***}	0.01	-0.01^{*}
	(0.01)	(0.01)	(0.01)	(0.00)	(0.00)
R^2	0.16	0.21	0.16	0.27	0.07
Num. obs.	158	158	158	158	158
F statistic	5.93	8.28	5.67	10.97	2.27
[B] *Industry*					
ROB Exposure	0.01^{*}	0.00	0.02	0.05^{***}	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.01)
R^2	0.13	0.14	0.53	0.14	0.51
Num. obs.	158	158	158	158	158
F statistic	4.61	5.02	34.44	4.84	31.28
[C] *Services*					
ROB Exposure	0.04^{***}	0.06^{***}	0.08^{***}	0.13^{***}	-0.10^{***}
	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)
R^2	0.37	0.43	0.22	0.52	0.37
Num. obs.	158	158	158	158	158
F statistic	17.64	22.71	8.53	32.45	17.82

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.5: Impact of Robots on Sectoral Average Wage.

	OLS Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] *Agriculture*					
ROB Exposure	-1.49^{***}	-1.53^{***}	-3.07^{***}	-0.13	0.37
	(0.21)	(0.25)	(0.54)	(0.25)	(0.32)
R^2	0.43	0.44	0.33	0.19	0.34
Num. obs.	156	156	157	157	157
F statistic	22.85	23.66	14.56	7.12	15.75
[B] *Industry*					
ROB Exposure	-0.10	0.01	-0.21	-0.20^{**}	0.09
	(0.08)	(0.09)	(0.18)	(0.09)	(0.12)
R^2	0.32	0.35	0.19	0.43	0.18
Num. obs.	158	158	158	158	158
F statistic	14.53	16.72	7.01	22.87	6.46
[C] *Services*					
ROB Exposure	-0.10	-0.26^{***}	-0.76^{***}	-0.07^{*}	0.53^{***}
	(0.07)	(0.06)	(0.12)	(0.04)	(0.07)
R^2	0.23	0.34	0.26	0.47	0.34
Num. obs.	158	158	158	158	158
F statistic	8.95	15.65	10.74	27.34	15.40

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral 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 ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.6: Impact of Digital Technologies on Sectoral Employment Rate. ICT Phases

	OLS Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
ICT Exposure	-0.00	0.00	0.00	-0.01	0.00	0.00	0.00	0.00
	(0.00)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.00)
SDB Exposure	0.01^{**}	0.05^{***}	0.04^{***}	0.02^{*}	-0.01	-0.00	0.01	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.16	0.24	0.12	0.13	0.12	0.04	0.06	0.07
Num. obs.	158	158	158	158	158	158	158	158
F statistic	5.93	9.77	4.05	4.39	4.31	1.42	2.09	2.27
[B] *Industry*								
ICT Exposure	-0.00	-0.02^{*}	0.00	-0.09^{***}	-0.09^{***}	-0.01	-0.13^{***}	-0.00
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
SDB Exposure	0.00	-0.05^{***}	-0.10^{***}	-0.06^{***}	-0.02	-0.02	-0.06^{***}	-0.03^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
R^2	0.13	0.56	0.47	0.40	0.40	0.35	0.83	0.51
Num. obs.	158	158	158	158	158	158	158	158
F statistic	4.61	39.28	26.71	20.50	20.61	16.04	146.05	31.28
[C] *Services*								
ICT Exposure	0.02^{**}	0.03^{*}	0.00	-0.05	-0.01	0.10^{***}	-0.14^{***}	-0.02
	(0.01)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.02)
SDB Exposure	-0.03^{*}	-0.00	0.09^{***}	-0.04	-0.02	0.03^{**}	-0.10^{***}	-0.08^{***}
	(0.01)	(0.02)	(0.03)	(0.04)	(0.02)	(0.02)	(0.03)	(0.03)
R^2	0.37	0.32	0.16	0.09	0.62	0.41	0.74	0.37
Num. obs.	158	158	158	158	158	158	158	158
F statistic	17.64	14.35	5.72	3.00	50.37	21.52	86.34	17.82

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.7: Impact of ICT and SDB on Sectoral Average Wage.

	OLS Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
ICT Exposure	0.80^{***}	-0.51	-0.82	2.13^{***}	0.31	-0.38	-0.25	0.10
	(0.16)	(0.36)	(0.56)	(0.77)	(0.33)	(0.36)	(0.72)	(0.31)
SDB Exposure	-0.14	1.11^{***}	0.60	0.92	0.12	0.55	0.29	-1.59^{***}
	(0.20)	(0.42)	(0.62)	(0.69)	(0.36)	(0.34)	(0.54)	(0.39)
R^2	0.43	0.39	0.34	0.12	0.23	0.03	0.30	0.34
Num. obs.	156	157	157	158	157	157	157	157
F statistic	22.85	19.30	15.49	4.00	9.05	0.84	12.90	15.75
[B] *Industry*								
ICT Exposure	0.26^{***}	0.35^{***}	0.57^{***}	0.85^{***}	0.30^{**}	0.20	1.00^{***}	-0.04
	(0.06)	(0.13)	(0.18)	(0.15)	(0.12)	(0.12)	(0.26)	(0.12)
SDB Exposure	0.09	0.35^{**}	0.57^{***}	0.17	0.06	0.28^{**}	-0.49^{**}	0.25^{*}
	(0.08)	(0.16)	(0.20)	(0.13)	(0.13)	(0.12)	(0.20)	(0.14)
R^2	0.32	0.28	0.17	0.36	0.21	0.31	0.30	0.18
Num. obs.	158	158	158	158	158	158	158	158
F statistic	14.53	11.60	6.01	16.86	8.29	13.59	13.03	6.46
[C] *Services*								
ICT Exposure	0.14^{**}	0.26^{***}	0.09	0.61^{***}	-0.05	0.25^{***}	-0.09	-0.24^{***}
	(0.05)	(0.09)	(0.11)	(0.10)	(0.05)	(0.06)	(0.15)	(0.07)
SDB Exposure	0.17^{***}	-0.15	-0.29^{**}	0.04	0.15^{***}	-0.00	0.10	0.31^{***}
	(0.06)	(0.11)	(0.12)	(0.09)	(0.05)	(0.05)	(0.11)	(0.08)
R^2	0.23	0.32	0.22	0.48	0.54	0.15	0.58	0.34
Num. obs.	158	158	158	158	158	158	158	158
F statistic	8.95	14.04	8.80	28.51	35.97	5.20	41.36	15.40

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 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 sectoral 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 robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.8: Impact of Digital Technologies on Sectoral Employment Rate. Digital Technologies Phases

	OLS Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
DIG Exposure	0.02^{***}	0.05^{***}	0.04^{***}	0.02	-0.01^{**}	-0.00	-0.00	0.00
	(0.01)	(0.01)	(0.01)	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
R^2	0.18	0.26	0.11	0.12	0.14	0.04	0.06	0.07
Num. obs.	158	158	158	158	158	158	158	158
F statistic	8.50	13.23	4.75	4.98	6.48	1.71	2.23	2.84
[B] *Industry*								
DIG Exposure	-0.00	-0.06^{***}	-0.07^{***}	-0.08^{***}	-0.10^{***}	-0.02	-0.11^{***}	-0.04^{***}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.01)
R^2	0.13	0.55	0.43	0.32	0.39	0.34	0.78	0.52
Num. obs.	158	158	158	158	158	158	158	158
F statistic	5.77	46.83	28.91	18.07	24.41	19.78	138.88	41.32
[C] *Services*								
DIG Exposure	0.03^{**}	0.08^{***}	0.12^{***}	-0.05	-0.00	0.13^{***}	-0.18^{***}	-0.10^{***}
	(0.01)	(0.02)	(0.03)	(0.04)	(0.01)	(0.02)	(0.02)	(0.02)
R^2	0.37	0.36	0.19	0.08	0.62	0.47	0.72	0.38
Num. obs.	158	158	158	158	158	158	158	158
F statistic	22.59	21.98	8.98	3.35	61.53	33.77	97.68	23.71

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.9: Impact of Digital Technologies on Sectoral Average Wage.

	OLS Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
DIG Exposure	0.47^{**}	0.36	-0.35	2.47^{***}	0.64^{**}	-0.23	1.18^{***}	-1.23^{***}
	(0.20)	(0.43)	(0.63)	(0.76)	(0.25)	(0.38)	(0.44)	(0.31)
R^2	0.36	0.36	0.33	0.12	0.25	0.01	0.33	0.32
Num. obs.	156	157	157	158	157	157	157	157
F statistic	20.81	21.55	18.53	5.02	12.82	0.28	18.64	17.70
[B] *Industry*								
DIG Exposure	0.25^{***}	0.34^{**}	0.74^{***}	0.37^{**}	0.47^{***}	0.28^{**}	0.52^{***}	0.14
	(0.08)	(0.16)	(0.20)	(0.16)	(0.09)	(0.13)	(0.17)	(0.11)
R^2	0.25	0.23	0.13	0.23	0.29	0.29	0.28	0.16
Num. obs.	158	158	158	158	158	158	158	158
F statistic	12.42	11.20	5.82	11.40	15.37	15.54	14.71	7.51
[C] *Services*								
DIG Exposure	0.03	-0.21^{**}	-0.54^{***}	0.20^{*}	0.05	-0.03	0.16^{*}	0.03
	(0.06)	(0.11)	(0.12)	(0.11)	(0.04)	(0.06)	(0.09)	(0.07)
R^2	0.09	0.29	0.29	0.37	0.52	0.04	0.58	0.26
Num. obs.	158	158	158	158	158	158	158	158
F statistic	3.97	15.95	15.48	22.56	40.94	1.54	53.39	13.63

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral 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 robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

C.2 First Stage IV Regressions

Table C.10: First-Stage Regression Robot Breakthroughs (Robots)

	First Stage IV Regression – Dep. var.: ROB Exposure				
	All	Robotics			Intelligent Robots
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
Intercept	-1.30^{***}	-1.08^{***}	-0.55^{***}	-0.53^{***}	-0.22^{**}
	(0.31)	(0.23)	(0.10)	(0.14)	(0.09)
ROB Exposure (US)	1.71^{***}	1.92^{***}	3.08^{***}	1.38^{***}	1.16^{***}
	(0.13)	(0.14)	(0.19)	(0.13)	(0.13)
R^2	0.52	0.55	0.62	0.43	0.33
Num. obs.	158	158	158	158	158
F statistic	165.70	190.90	257.96	117.07	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. Regressions are weighted by the population in 1980.

Table C.11: First-Stage Regression Digital Technologies Breakthroughs (ICT)

	First Stage IV Regression – Dep. var.: ICT Exposure							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
Intercept	-0.25	0.27^{**}	0.23^{*}	0.03	-0.21	0.04	-0.21	-0.22^{**}
	(0.27)	(0.13)	(0.12)	(0.03)	(0.17)	(0.11)	(0.16)	(0.10)
ICT Exposure (US)	0.21^{***}	0.26^{***}	0.29^{***}	0.19^{***}	0.18^{***}	0.20^{***}	0.15^{**}	0.18^{***}
	(0.03)	(0.06)	(0.08)	(0.04)	(0.04)	(0.06)	(0.07)	(0.04)
R^2	0.24	0.10	0.07	0.11	0.11	0.08	0.03	0.14
Num. obs.	158	158	158	158	158	158	158	158
F statistic	49.57	17.31	12.04	18.59	19.85	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. Regressions are weighted by the population in 1980.

Table C.12: First-Stage Regression Digital Technologies Breakthroughs (Software & Database)

	First Stage IV Regression – Dep. var.: SDB Exposure							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
Intercept	-0.39	0.32^{**}	0.01	0.23^{***}	-0.51^{**}	-0.24^{*}	-0.23^{*}	-0.16
	(0.45)	(0.16)	(0.14)	(0.04)	(0.25)	(0.12)	(0.14)	(0.11)
SDB Exposure (US)	0.55^{***}	0.43^{***}	0.55^{***}	0.23^{***}	0.58^{***}	0.67^{***}	0.48^{***}	0.60^{***}
	(0.07)	(0.08)	(0.10)	(0.08)	(0.09)	(0.09)	(0.10)	(0.07)
R^2	0.28	0.16	0.17	0.05	0.21	0.25	0.13	0.29
Num. obs.	158	158	158	158	158	158	158	158
F statistic	59.46	29.10	32.57	8.27	41.04	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. Regressions are weighted by the population in 1980.

C.3 Second Stage (IV) Regressions

Table C.13: Impact of Robots during Robot Cycles

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] Δ *Employment-to-population* × *100*					
ROB Exposure	0.11^{***}	0.12^{***}	0.22^{***}	0.06	0.07^{**}
	(0.03)	(0.04)	(0.07)	(0.05)	(0.03)
R^2	0.61	0.60	0.70	0.79	0.82
Num. obs.	158	158	158	158	158
F statistic	13.00	12.38	19.38	30.53	36.31
[B] Δ *Average wage (in log)* × *100*					
ROB Exposure	0.00	-0.11	-0.12	0.11	0.40^{***}
	(0.12)	(0.14)	(0.25)	(0.11)	(0.08)
R^2	0.66	0.70	0.63	0.72	0.65
Num. obs.	158	158	158	158	158
F statistic	15.71	19.12	13.94	21.66	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 change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.14: Impact of Digital Technologies during Digital Cycles

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*								
DIG Exposure	0.00	-0.09^{***}	0.18^{***}	-0.13^{*}	-0.02	-0.01	0.01	0.00
	(0.01)	(0.03)	(0.06)	(0.07)	(0.03)	(0.04)	(0.03)	(0.03)
R^2	0.59	0.77	0.59	0.63	0.87	0.66	0.91	0.82
Num. obs.	158	158	158	158	158	158	158	158
F statistic	12.57	28.89	12.68	14.89	59.83	17.20	89.58	38.85
[B] Δ *Average wage (in log)* $\times$ *100*								
DIG Exposure	-0.00	0.24^{**}	-0.18	0.43^{***}	0.08	0.20^{**}	-0.01	0.36^{***}
	(0.05)	(0.11)	(0.18)	(0.15)	(0.05)	(0.10)	(0.07)	(0.07)
R^2	0.63	0.71	0.46	0.81	0.75	0.67	0.89	0.65
Num. obs.	158	158	158	158	158	158	158	158
F statistic	14.80	21.63	7.42	38.48	26.74	17.98	73.38	16.02

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 (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.15: Impact of ICT and SDB during Digital Technology Cycles

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*								
ICT Exposure	0.05^{***}	0.22^{***}	0.62^{***}	-0.71^{***}	-0.04	-0.01	-0.10^{***}	-0.00
	(0.02)	(0.07)	(0.12)	(0.27)	(0.03)	(0.05)	(0.04)	(0.03)
SDB Exposure	-0.06^{***}	-0.29^{***}	-0.37^{***}	0.38^{**}	0.03	-0.00	0.10^{***}	0.00
	(0.02)	(0.06)	(0.11)	(0.19)	(0.04)	(0.05)	(0.03)	(0.03)
R^2	0.61	0.79	0.64	0.64	0.87	0.66	0.92	0.82
Num. obs.	158	158	158	158	158	158	158	158
F statistic	13.00	30.82	14.92	14.85	56.59	16.07	90.92	36.31
[B] Δ *Average wage (in log)* $\times$ *100*								
ICT Exposure	-0.23^{***}	-0.78^{***}	-1.43^{***}	0.78	0.03	0.06	-0.03	0.26^{***}
	(0.07)	(0.25)	(0.38)	(0.58)	(0.06)	(0.14)	(0.09)	(0.09)
SDB Exposure	0.26^{***}	0.98^{***}	1.09^{***}	-0.16	0.05	0.14	0.02	0.12
	(0.08)	(0.24)	(0.34)	(0.41)	(0.07)	(0.12)	(0.08)	(0.07)
R^2	0.66	0.74	0.50	0.82	0.75	0.67	0.89	0.65
Num. obs.	158	158	158	158	158	158	158	158
F statistic	15.71	22.86	8.31	36.29	24.99	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 change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.16: Impact of Robots on Sectoral Employment Rate. Robot Phases

	IV Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] *Agriculture*					
ROB Exposure	0.01	0.02	0.02	0.00	-0.01^{*}
	(0.01)	(0.01)	(0.03)	(0.01)	(0.01)
R^2	0.50	0.54	0.34	0.53	0.36
Num. obs.	158	158	158	158	158
F statistic	8.32	9.52	4.23	9.36	4.73
[B] *Industry*					
ROB Exposure	0.01	0.02	-0.00	0.02	-0.01
	(0.01)	(0.02)	(0.03)	(0.02)	(0.01)
R^2	0.57	0.64	0.85	0.87	0.72
Num. obs.	158	158	158	158	158
F statistic	11.04	14.95	46.09	56.31	21.04
[C] *Services*					
ROB Exposure	0.09^{***}	0.08^{**}	0.20^{***}	0.04	0.09^{***}
	(0.03)	(0.03)	(0.06)	(0.04)	(0.03)
R^2	0.67	0.66	0.52	0.68	0.72
Num. obs.	158	158	158	158	158
F statistic	16.52	16.22	8.93	17.28	21.03

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

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Table C.17: Impact of Robots on Sectoral Average Wage.

	IV Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] *Agriculture*					
ROB Exposure	0.04	0.13	-1.01	0.23	0.53
	(0.42)	(0.55)	(1.31)	(0.68)	(0.44)
R^2	0.66	0.70	0.52	0.48	0.66
Num. obs.	156	156	157	157	157
F statistic	15.77	18.94	8.73	7.64	16.18
[B] *Industry*					
ROB Exposure	0.10	-0.01	-0.29	0.38^{*}	0.23
	(0.15)	(0.19)	(0.38)	(0.21)	(0.14)
R^2	0.66	0.69	0.58	0.70	0.68
Num. obs.	158	158	158	158	158
F statistic	16.03	18.57	11.22	19.44	17.89
[C] *Services*					
ROB Exposure	-0.01	-0.14	-0.07	0.11	0.33^{***}
	(0.10)	(0.12)	(0.22)	(0.11)	(0.09)
R^2	0.72	0.73	0.69	0.69	0.69
Num. obs.	158	158	158	158	158
F statistic	21.67	21.92	18.34	18.32	18.30

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral 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 ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.18: Impact of Digital Technologies on Sectoral Employment Rate. Digital Technologies Phases

	IV Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
DIG Exposure	0.03^{***}	0.03^{**}	0.06^{***}	-0.04^{**}	0.01	-0.00	-0.01	-0.01^{*}
	(0.01)	(0.01)	(0.02)	(0.02)	(0.00)	(0.01)	(0.01)	(0.01)
R^2	0.47	0.46	0.29	0.46	0.47	0.40	0.28	0.36
Num. obs.	158	158	158	158	158	158	158	158
F statistic	7.78	7.37	3.54	7.65	7.87	5.95	3.41	5.05
[B] *Industry*								
DIG Exposure	-0.02^{***}	-0.04^{***}	-0.02	-0.07^{**}	-0.01	-0.04^{**}	-0.02^{*}	-0.00
	(0.01)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.01)
R^2	0.57	0.88	0.83	0.67	0.92	0.82	0.93	0.71
Num. obs.	158	158	158	158	158	158	158	158
F statistic	11.77	64.96	42.85	17.99	95.67	39.85	120.16	22.06
[C] *Services*								
DIG Exposure	-0.00	-0.08^{***}	0.14^{***}	-0.02	-0.02	0.04	0.03	0.02
	(0.01)	(0.02)	(0.05)	(0.06)	(0.02)	(0.03)	(0.03)	(0.02)
R^2	0.66	0.58	0.38	0.58	0.74	0.67	0.81	0.72
Num. obs.	158	158	158	158	158	158	158	158
F statistic	17.00	11.99	5.36	12.30	25.15	17.74	36.51	22.43

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.19: Impact of Digital Technologies on Sectoral Average Wage.

	IV Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
DIG Exposure	0.23	0.26	-2.28^{**}	0.48	0.26	-0.45	0.07	-0.25
	(0.18)	(0.49)	(0.94)	(0.98)	(0.30)	(0.61)	(0.40)	(0.38)
R^2	0.66	0.60	0.49	0.68	0.67	0.39	0.72	0.66
Num. obs.	156	157	157	158	157	157	157	157
F statistic	16.83	12.86	8.46	18.58	17.43	5.69	22.96	17.27
[B] *Industry*								
DIG Exposure	0.07	0.31^{**}	-0.10	0.50^{**}	0.06	0.39^{*}	-0.16	0.01
	(0.07)	(0.16)	(0.26)	(0.23)	(0.11)	(0.21)	(0.14)	(0.12)
R^2	0.64	0.64	0.51	0.66	0.66	0.58	0.76	0.68
Num. obs.	158	158	158	158	158	158	158	158
F statistic	15.85	15.34	9.15	17.16	17.05	12.14	27.40	18.87
[C] *Services*								
DIG Exposure	0.05	0.29^{***}	-0.02	0.32^{**}	0.11^{**}	0.24^{***}	-0.00	0.38^{***}
	(0.05)	(0.10)	(0.16)	(0.14)	(0.05)	(0.09)	(0.08)	(0.08)
R^2	0.71	0.72	0.57	0.77	0.72	0.49	0.85	0.69
Num. obs.	158	158	158	158	158	158	158	158
F statistic	21.13	23.07	11.58	29.36	22.54	8.51	50.67	19.20

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 of digital technologies (ICT and SDB aggregated), are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral 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 robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.20: Impact of Digital Technologies on Sectoral Employment Rate. ICT Phases

	IV Reg. - Dep. var.: Annualized Δ Employment-to-population $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
ICT Exposure	0.03^{***}	0.09^{***}	0.07	0.09	0.01^{***}	0.01	-0.00	-0.01
	(0.01)	(0.03)	(0.04)	(0.07)	(0.01)	(0.01)	(0.01)	(0.01)
SDB Exposure	-0.01	-0.06^{**}	-0.00	-0.10^{**}	-0.01	-0.01	-0.01	-0.00
	(0.01)	(0.03)	(0.04)	(0.05)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.50	0.49	0.29	0.47	0.49	0.41	0.28	0.36
Num. obs.	158	158	158	158	158	158	158	158
F statistic	8.32	7.90	3.38	7.42	7.90	5.67	3.20	4.73
[B] *Industry*								
ICT Exposure	-0.01	-0.02	-0.02	0.01	0.01	-0.00	-0.01	-0.02
	(0.01)	(0.03)	(0.04)	(0.12)	(0.01)	(0.03)	(0.01)	(0.01)
SDB Exposure	-0.02^{*}	-0.02	-0.01	-0.07	-0.02	-0.04^{*}	-0.01	0.01
	(0.01)	(0.03)	(0.04)	(0.08)	(0.02)	(0.02)	(0.01)	(0.01)
R^2	0.57	0.88	0.83	0.67	0.92	0.82	0.93	0.72
Num. obs.	158	158	158	158	158	158	158	158
F statistic	11.04	60.71	40.05	16.84	90.47	37.43	112.29	21.04
[C] *Services*								
ICT Exposure	0.03^{*}	0.15^{**}	0.57^{***}	-0.81^{***}	-0.07^{***}	-0.02	-0.09^{***}	0.02
	(0.02)	(0.06)	(0.10)	(0.22)	(0.02)	(0.04)	(0.03)	(0.03)
SDB Exposure	-0.04^{*}	-0.22^{***}	-0.37^{***}	0.55^{***}	0.06^{**}	0.05	0.11^{***}	-0.01
	(0.02)	(0.06)	(0.09)	(0.15)	(0.03)	(0.03)	(0.03)	(0.02)
R^2	0.67	0.61	0.48	0.62	0.75	0.67	0.83	0.72
Num. obs.	158	158	158	158	158	158	158	158
F statistic	16.52	12.62	7.57	13.42	25.29	16.76	39.09	21.03

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.21: Impact of ICT and SDB on Sectoral Average Wage.

	IV Reg. - Dep. var.: Annualized Δ Average wage (in log) $\times$ 100							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] *Agriculture*								
ICT Exposure	0.01	1.37	1.14	−5.22	0.09	−0.14	0.10	−0.33
	(0.25)	(1.21)	(2.09)	(3.79)	(0.36)	(0.88)	(0.48)	(0.45)
SDB Exposure	0.25	−1.04	−3.20*	4.06	0.19	−0.30	−0.01	0.06
	(0.29)	(1.16)	(1.87)	(2.69)	(0.42)	(0.77)	(0.42)	(0.38)
R^2	0.66	0.60	0.50	0.68	0.67	0.39	0.72	0.66
Num. obs.	156	157	157	158	157	157	157	157
F statistic	15.77	12.18	8.04	17.74	16.29	5.32	21.46	16.18
[B] *Industry*								
ICT Exposure	−0.19**	−0.42	−1.05*	2.81***	0.03	0.38	−0.26	−0.14
	(0.09)	(0.39)	(0.58)	(0.85)	(0.13)	(0.30)	(0.16)	(0.14)
SDB Exposure	0.30***	0.71*	0.83	−1.52**	0.03	0.05	0.07	0.13
	(0.10)	(0.37)	(0.52)	(0.61)	(0.15)	(0.26)	(0.14)	(0.12)
R^2	0.66	0.64	0.52	0.68	0.66	0.58	0.76	0.68
Num. obs.	158	158	158	158	158	158	158	158
F statistic	16.03	14.69	8.93	17.65	15.93	11.40	25.94	17.89
[C] *Services*								
ICT Exposure	−0.15**	−0.68***	−1.33***	0.49	0.04	0.06	0.02	0.35***
	(0.06)	(0.23)	(0.34)	(0.55)	(0.06)	(0.13)	(0.09)	(0.09)
SDB Exposure	0.23***	0.93***	1.16***	−0.05	0.07	0.18	−0.02	0.06
	(0.07)	(0.22)	(0.31)	(0.39)	(0.07)	(0.12)	(0.08)	(0.08)
R^2	0.72	0.75	0.61	0.77	0.72	0.49	0.85	0.69
Num. obs.	158	158	158	158	158	158	158	158
F statistic	21.67	24.35	12.97	27.54	21.08	7.99	47.37	18.30

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 in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 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 sectoral 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 robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

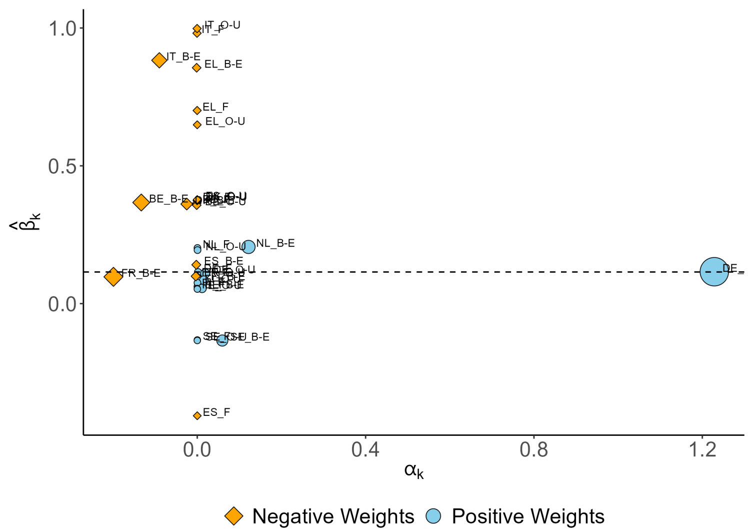
Summary of Results

Table C.22: Summary of the Net Employment Effects of Robots and Digital Technologies at the Regional Level

[A] *Robots*								
	All	Robotics						Intelligent Robots
	1995-2017	1995-2013	1995-2002	2002-2013				2013-2017
Total	Reinstate	Reinstate	Reinstate					Reinstate H
Agriculture								
Industry								
Services	Reinstate	Reinstate	Reinstate					Reinstate H
[B] *Digital Technologies*								
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
Total		Displace L	Reinstate	Sub L with H		Sub. L with H		
Agriculture	Reinstate	Reinstate L	Displace					
Industry	Displace	Displace L		Displace L		Displace		
Services		Displace L	Reinstate	Sub. L with H	Sub. L with H	Sub. L with H		Sub. L with H
[C] *Information and Communication Technology (ICT)*								
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
Total	Reinstate L	Reinstate L	Reinstate L	Displace			Displace	Sub L with H
Agriculture	Reinstate	Reinstate			Reinstate			
Industry	Sub. H with L		Sub. H with L	Sub. L with H				
Services	Reinstate L	Reinstate L	Reinstate L	Displace L	Displace L		Displace L	Sub. L with H
[D] *Software and Database (SDB)*								
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
Total	Displace L	Displace L	Displace L	Reinstate			Reinstate	
Agriculture		Displace		Displace				
Industry	Sub. L with H		Sub. H with L					
Services	Sub. L with H	Displace L	Displace L	Reinstate	Reinstate		Reinstate	

Notes: This Tables summarizes the IV coefficient results displayed in Tables C.13 to C.19.

Figure C.1: Heterogeneity in β_k for Robots



Notes: This figure plots the relationship between each instrument's and the Rotemberg weights for robots. Each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table C.13.

C.4 Validity and Robustness Checks

Rotemberg Weights

Table C.23: Summary of Rotemberg weights – ROB.

nace	g	alpha	beta	share
DE_B-E	16.093	1.229	0.116	63.950
FR_B-E	4.246	-0.199	0.097	10.364
BE_B-E	5.551	-0.133	0.367	6.923
NL_B-E	8.830	0.122	0.206	6.340
IT_B-E	6.789	-0.090	0.883	4.688

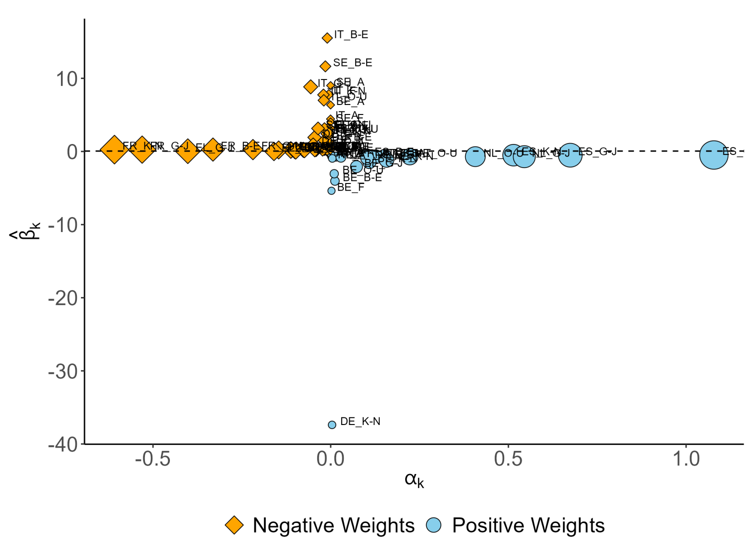
Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in robot stock while the third column (alpha α_k) reports the weights, the fourth column (beta) displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.24: Summary of Rotemberg weights – ICT.

nace	g	alpha	beta	share
ES_O-U	3.377	1.078	-0.484	13.609
ES_G-J	1.868	0.674	-0.512	8.508
FR_K-N	3.854	-0.608	0.251	7.679
NL_G-J	3.780	0.545	-0.715	6.875
FR_G-J	1.573	-0.531	0.250	6.696

Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in ICT stock in sector k while the third column (alpha α_k) reports the weights, the third column (beta) displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1980, the change in SDB and robots, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1980.

Figure C.2: Heterogeneity in β_k for information and communication technologies



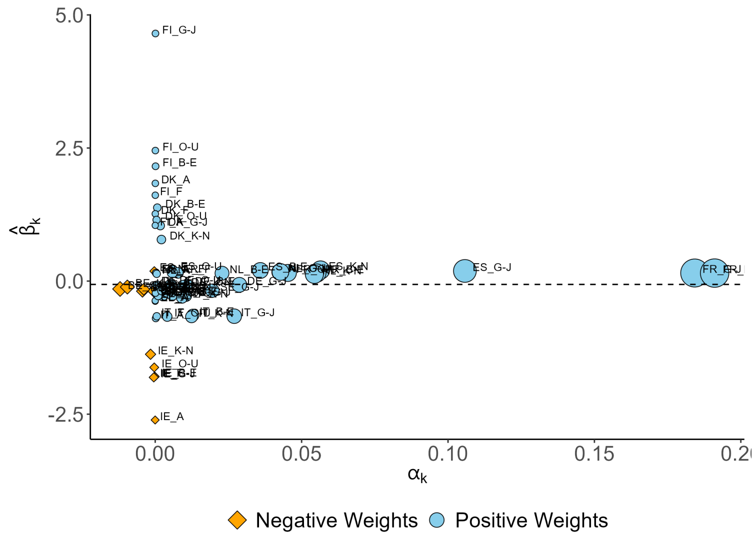
Notes: This figure plots the relationship between each instrument's and the Rotemberg weights for information and communication technologies, where each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table C.15.

Table C.25: Summary of Rotemberg weights – SDB.

nace	g	alpha	beta	share
FR_K-N	16.104	0.191	0.150	17.901
FR_G-J	7.337	0.184	0.152	17.264
ES_G-J	7.879	0.106	0.191	9.910
ES_K-N	13.479	0.056	0.207	5.289
FR_B-E	2.225	0.055	0.151	5.173

Notes: This table shows the top five country-industries (first column) according to the Rotemberg weights after implementing the decomposition of the IV estimator proposed by Goldsmith-Pinkham et al. (2020). The second column (g_k) represents the country-industry change in SDB stock while the third column (alpha α_k) reports the weights, the fourth column displays the just-identified coefficient estimates (β_k), and the fifth column indicates the proportion that the absolute value of each weight α_k contributes to the total sum of absolute values across all α_k. Control variables include the log of the population in 1980, the change in ICT and robots, final demand and trade exposure respectively over the period that goes from 1995-2017, and country fixed effects. Regressions are weighted by the population in 1980.

Figure C.3: Heterogeneity in β_k for software and database



Notes: This figure plots the relationship between each instrument's and the Rotemberg weights for software and database. Each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table C.15.

Further robustness checks

Table C.26: Impact of Robots during Robot Phases Excluding Germany

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2013	1995-2002	2002-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.11^{***}	0.13^{***}	0.17^{**}	0.07	0.07^{**}
	(0.04)	(0.04)	(0.08)	(0.06)	(0.03)
R^2	0.53	0.45	0.72	0.58	0.85
Num. obs.	128	128	128	128	128
F statistic	7.81	5.60	18.05	9.55	38.23
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	-0.08	-0.23	-0.10	0.01	0.39^{***}
	(0.13)	(0.15)	(0.28)	(0.11)	(0.09)
R^2	0.68	0.72	0.63	0.78	0.51
Num. obs.	128	128	128	128	128
F statistic	15.08	18.27	11.78	24.24	7.11

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 (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second column corresponds to the effect of the entire Robotics cycle, while the third and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980. The sample excludes German NUTS-2 regions.

Table C.27: Impact of ICT and SDB during Digital Technologies Cycles Excluding Spain

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable							
	All	Web 1.0			GraphUI - Cloud			Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	1995-2017	1995-2004	1995-2001	2001-2004	2004-2013	2004-2009	2009-2013	2013-2017
[A] Δ *Employment-to-population* $\times$ *100*								
ICT Exposure	0.06^{***}	0.25^{***}	0.50^{***}	-0.86^{***}	-0.02	0.06	-0.10^{**}	-0.02
	(0.02)	(0.07)	(0.11)	(0.29)	(0.03)	(0.05)	(0.04)	(0.03)
SDB Exposure	-0.05^{**}	-0.31^{***}	-0.45^{***}	0.47^{**}	0.03	-0.05	0.11^{***}	-0.01
	(0.02)	(0.06)	(0.09)	(0.21)	(0.03)	(0.04)	(0.03)	(0.03)
R^2	0.65	0.55	0.51	0.56	0.84	0.70	0.87	0.60
Num. obs.	139	139	139	139	139	139	139	139
F statistic	14.18	9.43	8.00	9.77	39.32	18.17	50.52	11.38
[B] Δ *Average wage (in log)* $\times$ *100*								
ICT Exposure	-0.19^{**}	-0.80^{***}	-1.25^{***}	0.86	0.05	0.04	-0.00	0.30^{***}
	(0.07)	(0.27)	(0.40)	(0.63)	(0.06)	(0.15)	(0.09)	(0.09)
SDB Exposure	0.18^{**}	0.96^{***}	1.16^{***}	-0.20	0.05	0.12	0.00	0.13^{*}
	(0.08)	(0.26)	(0.35)	(0.45)	(0.07)	(0.13)	(0.08)	(0.08)
R^2	0.68	0.73	0.53	0.81	0.77	0.59	0.89	0.67
Num. obs.	139	139	139	139	139	139	139	139
F statistic	16.29	20.46	8.75	31.83	24.91	11.17	63.83	15.77

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 (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and fifth columns correspond to the two entire cycles, while the third and fourth columns correspond to the phases of the Web 1.0 cycle, the sixth and seventh 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 information and communication (ICT), and software-database (SDB), are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robot, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980. The sample excludes Spanish NUTS-2 regions.

Table C.28: Impact of Automation Technologies – Pre-trends

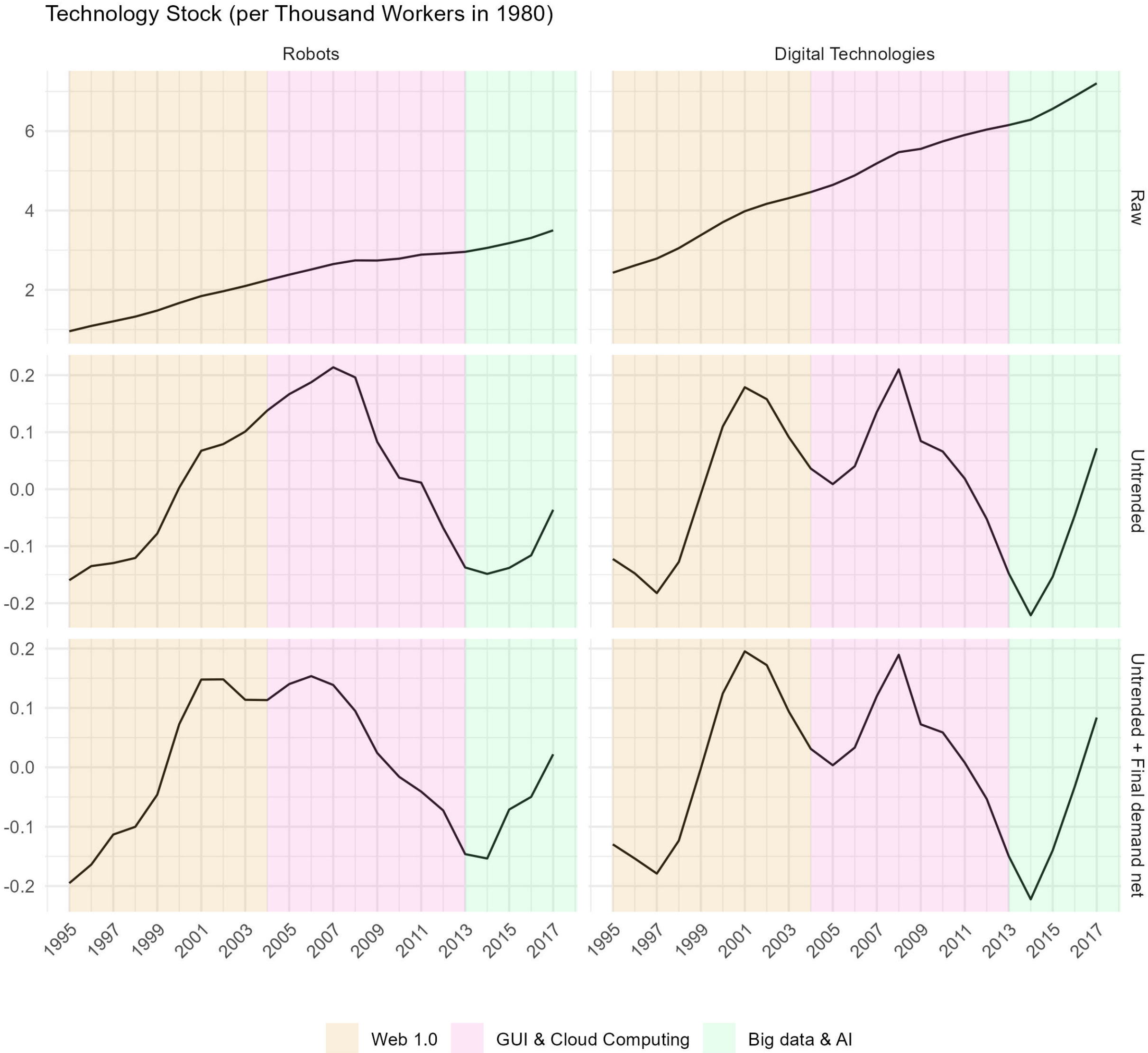
	IV Reg. - Δ Employment-to-population $\times$ 100	
	Pre-trend	1995-2001
ROB Exposure	0.06^{**}	0.15^{***}
	(0.03)	(0.04)
ICT Exposure	0.14^{*}	0.41^{***}
	(0.07)	(0.11)
SDB Exposure	-0.01	-0.34^{***}
	(0.08)	(0.11)
R^2	0.63	0.60
Num. obs.	158	158
F statistic	15.97	14.09

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. The first column reports the coefficients for the period 1983–1989 (Pre-trend) and the second column for 1995-2001. Coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, and country fixed effects. Regressions are weighted by the population in 1980.

D Additional Figures

Figure D.1 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.

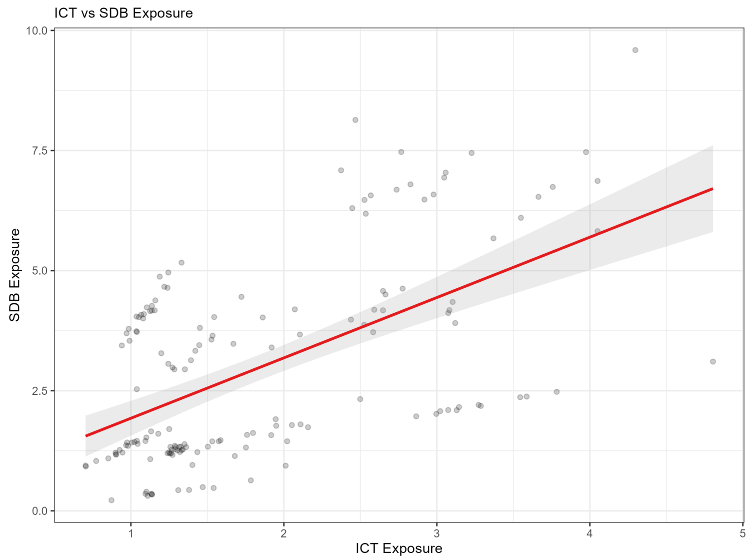
Figure D.1: Technology Stocks per Thousand Workers in 1980



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.

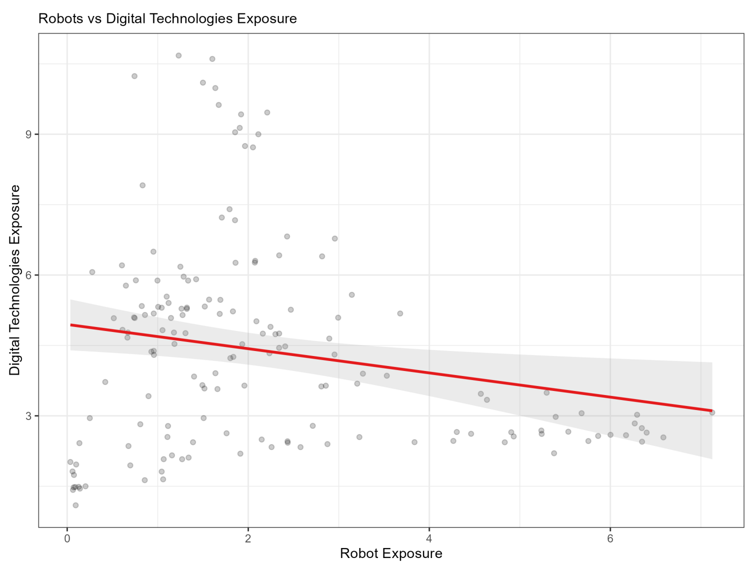
E Correlation Between Exposure To The Different Technologies

Figure E.1: Correlation between Software and Database and ICT Exposure. 1995-2017



Notes: This figure shows the correlation between the change in regional exposure to information and communication (ICT, x-axis), and software-database (SDB, y-axis) between 1995–2017. Exposure to ICT and SDB are calculated as shift-share.

Figure E.2: Correlation between Robots and Digital Technologies Exposure. 1995-2017



Notes: This figure shows the correlation between the change in regional exposure to robots (ROB, x-axis), and digital technologies (this is ICT & SDB aggregated, y-axis) between 1995–2017. Exposure to robots and digital technologies are calculated as shift-share.

F Technological Cycles: Summarizing Major Developments

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

Table F.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).

F.1 Web 1.0

Table F.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).[28] 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 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).

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

Table F.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).

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).

F.2 Graphical User Interface and Cloud Computing

Table F.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).

F.3 Big Data and Artificial Intelligence

Table F.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, 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).

Table F.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).

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).