UCL

CENTRE FOR EDUCATION POLICY
& EQUALISING OPPORTUNITIES

Working Paper No. 24-02

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

Florencia Jaccoud
UNU-MERIT

Fabien Petit
UCL

Tommaso Ciarli
UNU-MERIT

Maria Savona
University of Sussex

This paper examines the labor market implications of investment in automation over the life cycle of ICT and robot technologies from 1995 to 2017 in 163 European regions. We first identify major technological breakthroughs during this period and classify phases of acceleration and deceleration in investment. We then examine how exposure to automation technologies affects employment and wages across these different phases of their life cycle. We find that the negligible long-term impact of automation on employment conceals significant short-term positive and negative effects within phases of the technology life cycle. We also find that the negative impact of ICT investments on employment is driven by the phase of the cycle when investment decelerates (and the technology is more mature). The phases of the technology life cycles are more relevant than differences in regions' structural characteristics, such as productivity and sector specialization in explaining the impact of automation to on regional employment.

VERSION: February 2024

Suggested citation: Jaccoud, F., Petit, F., Ciarli, C., and Savona, M. (2024). *Automation and Employment over the Technology Life Cycle: Evidence from European Regions* (CEPEO Working Paper No. 24-02). Centre for Education Policy and Equalising Opportunities, UCL.

Highlights

- Technological advancements typically evolve through incremental changes interspersed with breakthrough innovations which lead to the emergence of technology life cycles.
- We explore how short-term impacts on European regional labour markets differ across the technology life cycles of four technologies: robots, information technologies, communication technologies, and software and databases.
- We find that while the long-term impacts of automation technologies on regional employment-to-population ratios are negligible, they mask significant short-term effects.
- We find that the nature of the impact on labour markets may be contingent on the specific technology life cycle phase.
- We find that the impact of automation on employment is influenced more by the technology life cycle phase than by regional structural differences such as sector specialization and productivity.

Why does this matter?

Policy should not ignore the short-term effects of automation since these differ among technologies and from the long-term effects.

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

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

February 2024

Abstract

This paper examines the labor market implications of investment in automation over the life cycle of ICT and robot technologies from 1995 to 2017 in 163 European regions. We first identify major technological breakthroughs during this period for these automation technologies and identify the phases of acceleration and deceleration in investment. We then examine how exposure to these automation technologies affects employment and wages across these different phases of their life cycle. We find that the negligible long term impact of automation on employment conceals significant short term positive and negative effects within phases of the technology life cycle. We also find that the negative impact of ICT investment on employment is driven by the phase of the cycle when investment decelerates (and the technology is more mature). The phases of the technology life cycles are more relevant than differences in regions' structural characteristics, such as productivity and sector specialization in explaining the impact of automation on regional employment.

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

*We are grateful to Elodie Andrieu, Filippo Bontadini, Angelo Cuzzola, Teresa Farinha, Neil Foster-McGregor, Önder Nomaler, Ekaterina Prytkova, Bart Verspagen as well as to audiences at the DRUID 2023, Eu-SPRI Conference 2023, Venice Summer Institute 2023, UNTANGLED final workshop, GEOINNO 2024, and the participants at the Social Situation Monitor 2020-24 seminar for useful comments and suggestions. We acknowledge the financial support of the European Union's Horizon 2020 research and innovation programme under agreement No 101004703 (PILLARS – Pathways to Inclusive Labour Markets).

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

[‡]University College London, CEPEO. Email: f.petit@ucl.ac.uk. Website: fabienpetit.com.

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

[¶]University of Sussex, SPRU. Email: m.savona@sussex.ac.uk.

1 Introduction

The increased codification of tasks introduces the potential for the displacement of workers responsible for performing these tasks by automation technologies (Simon 1960). In turn, the demand for jobs to perform these tasks diminishes (Autor et al. 2003). However, the literature suggests that over the long term, short-term changes in demand for labor due to task codification are likely to be offset by enhanced productivity and economic growth (Aghion et al. 2022), increased demand for final goods (Vivarelli 1995), and the creation of new tasks (Autor et al. 2022). An underexplored question is to what extent different vintages of automation technologies, each codifying more tasks, have affected labor markets in the short term, and whether their impact differs for different phases of adoption of each vintage, as firms and workers adapt to the new vintages.

In this paper, we explore how short-term impacts on European regional labor markets differ across the technology life cycles of four technologies: robots, information technologies (IT), communication technologies (CT), and software and databases (SDB). We first identify the main breakthrough technologies within these four groups and delineate their respective life cycles. We then estimate the impact of exposure to each phase of these technology life cycles on regional labor markets. This involves distinguishing between the initial period of accelerated adoption and the subsequent period of decelerated adoption, which precedes the next technological breakthrough.

Technological advancements typically evolve through incremental changes interspersed with breakthrough innovations which lead to the emergence of technology life cycles (Tushman and Anderson 1986). These cycles begin with rapid developments in various configurations and applications and culminate in the establishment of a dominant design (Abernathy and Utterback 1978). Standardization of the technology is followed first by a period of incremental changes and growing adoption, and then by a decline in both innovative activity and adoption rates which herald the next breakthrough innovation and subsequent life cycle. The pattern of diffusion of the breakthrough technology repeats this cycle: following establishment of the dominant design adoption grows exponentially then slows as diffusion of the technology reaches and overtakes the midpoint of potential adopter saturation (Geroski 2000).

Codification of the tasks and the skills required to work with the new technologies also change over the technology life cycle (Langlois 2003, Vona and Consoli 2015) which has at least two implications for research into the short-term impacts of automation on labor markets. First, the impacts may vary across different breakthrough technologies (Prytkova et al.

2024).[1] For instance, mechanical automation, robotic automation, and intelligent robotics perform different tasks with varying abilities and connectivity within the organization, and have different implications for employment within and outside manufacturing firms (Zuboff 1988).

Second, the direction and intensity of labor market impacts may vary over the technology life cycle. At least two opposing scenarios can be envisioned. In the first scenario, during the initial phase of the technology life cycle, firms hoard workers (Domini et al. 2021). This may be because in the early stages of development and adoption of the technology, the routinization of tasks is imperfect and requires adjustments. In this situation, technicians are important(Lewis 2020) and since the retraining of existing workers is costly and time-consuming (David 1985), firms reconfigure their production organization (Ciarli et al. 2021, Battisti et al. 2023) including the division of labor (Langlois 2003). In the final stages of the life cycle, the technology is mature and is more standardized, and firms have learned to integrate it efficiently into the production process and to perform many of the tasks previously carried out by workers.[2] In the second scenario, early adopters (which tend to be the most productive and technologically advanced firms, most capable of rapidly integrating new technologies) may replace workers. In turn, adoption of the technology by early adopters may lead to production expansion, potentially increasing demand for workers during the more mature stages of the technology life cycle (Vivarelli 1995). Ultimately, the scenario that prevails is likely to depend on the specific existing technologies and breakthrough technology involved.

In this paper, we study the impacts on regional labor markets of different groups of technologies and their life cycle phases. We empirically examine which effect prevails in a sample of 163 NUTS-2 regions from 12 European countries during the period 1995 to 2017. Because data on firm adoption across EU regions are not available, to proxy for the adoption life cycle at the regional level we use information on aggregate investment in each of the four groups of technologies. To implement our empirical analysis, we integrate data from multiple sources. We use EU-KLEMS to measure investment in IT and CT, and SDB (Release 2021), International Federation of Robotics (IFR) data to measure investment in robots, and ARDECO to assess labor market outcomes (Release 2021).

In the first stage of our two-stage analysis, we identify technology life cycles from 1995 to

[1]Tushman and Anderson (1986) and successive work suggests that technological breakthroughs can be competence-enhancing or destroying depending on which firms introduce the innovation. This affects the knowledge and skills that are replaced, reconfiguring the demand for jobs.

[2]For instance, Vona and Consoli (2015) note: "the degree of substitutability between workers and machines increases with incremental technological developments so long as the division of labor facilitates the standardization of a higher fraction of tasks."

2017, based on the history of major technological developments and variations in EU investment in robots, CT, IT, and SDB. We identify major technological breakthroughs during this period based on fluctuations in technology investments. Notably, we identify three concurrent life cycles for CT, IT, and SDB, reflecting the main information and communication technology (ICT) digital eras since the 1990s: World Wide Web (WWW) 1.0 (1990–2004), Graphical User Interface and Cloud Computing (2004–2012), and Big Data and Artificial Intelligence (AI) (2013–).

Our analysis also identifies a single extended technology life cycle in the case of robots spanning 1995 to 2012 and aligned with advancements in industrial robots in terms of enhanced articulation and mobility capabilities enabled by sensors. Starting in 2013, a second robot technology cycle has emerged, coinciding with the breakthroughs in big data and AI which have also impacted the ICT and SDB technology cycles.

In the second step of our analysis, we assess the impact of these automation technologies on various regional labor market outcomes during distinct technology life cycle phases. Specifically, we estimate the influence of regional exposure to these technologies on employment, employment-to-population ratio, and average wage.

To determine the effects of regional exposure to each technology, we adopt a shift-share instrumental variables (IV) approach which has been used in several previous studies (Chiacchio et al. 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, Dauth et al. 2021). This approach is tailored to our identified technology life cycles. We use investment in these technologies in the US as an instrument to address potential endogeneity in European exposure.

Categorizing regions based on their productive structures and productivity levels in 1980 (i.e. before our period of analysis) allows us to investigate whether the impacts of these technologies vary with regional characteristics. Our investigation spans the life cycle phases identified in the first stpe for robots, CT, IT, and SDB.

The analysis yields four main results. First, we observe that while the long-term impacts of automation technologies on regional employment-to-population ratios are negligible, they mask significant short-term effects. Specifically, the short-term negative impacts of ICT and SDB on regional employment-to-population ratios within their technology cycles dissipate over the long run. In the case of robots, the alternating positive and negative short-term effects across different phases of the robot technology life cycle are almost balanced but show a small long-term positive effect. This result is in line with the literature which provides mixed results for European regions and confirms that over the long term, automation does not universally displace human labor (Autor 2015). However, it underscores the importance of short-term impacts such as the average reduction in the employment-to-population ratio of 1-2 percentage points annually during the various phases of ICT investment.

Second, we show that different technological breakthroughs within the same technology group have different impacts on the employment-to-population ratio. This suggests that estimates of the impact of robots and ICT during periods that experience several technological innovations, may be the result of different, potentially contrasting impacts.

Third, our findings suggest that the nature of the impact on labor markets may be contingent on the specific technology life cycle phase. For instance, the negative impact on the employment-to-population ratio of exposure to ICT and SDB during the phases in the graphical user interface cloud computing life cycles is observed predominantly in the second more mature phase of these technologies. In this phase firms typically invest in more mature technology vintages. These results imply that in the case of ICT, firms required time to integrate the technologies effectively into their operations, before leading to task routinization and worker substitution. Additionally, the pronounced negative effect in this mature phase might be attributable to firms' adoption of more standardized technologies and employment of high-skilled workers replacing those performing routinized tasks.

In the case of robots, there is no evidence of a similar pattern. In contrast to ICT and SDB, during the third phase of the first cycle for robots which is characterized by technology maturity, lower prices, and slowdown in investment rates, regional employment and the employment-to-population ratio increase, which would suggest that regions with higher adoption experience increased sales.[3]

Fourth, we find that the impact of automation on employment is influenced more by the technology life cycle phase than by regional structural differences such as sector specialization and productivity. While the magnitude of the impact of automation varies across regions with different levels of productivity and labor specialization, the direction of the impact is consistent across these regions. This finding underscores the dominant role of the technology life cycle phase in shaping the labor market effects of automation and shows that it transcends regional structural variations.

This paper contributes to a large literature on the impact of automation technologies on labor markets (Goos et al. 2014, Chiacchio et al. 2018, Graetz and Michaels 2018, Aghion et al. 2019, Acemoglu and Restrepo 2020, Gregory et al. 2022). These studies focus predominantly on the long-term consequences of technology at various levels of analysis. Research on the US generally indicates a negative impact of robots on employment (Acemoglu and Restrepo 2020) while in the European case the findings are more mixed. For example, Acemoglu et al. (2020) report negative employment impacts from investment in robots, (Dauth et al. 2021) find no significant effects, and (Reljic et al. 2023) observe a positive impact.

[3] To clarify, we do not distinguish firm adoption but rely on instrumented estimates of regional investment.

Additionally, studies which differentiate among robots, CT, IT, and SDB report a range of effects that vary based on the specific technology and the industry involved (Blanas 2023; Jestl 2024). Finally, research focusing on different time periods reveals varying impacts, contingent on whether substitution or compensation effects dominate. For example, Antón et al. (2022) note that the slight negative effect of robots on employment during 1995–2005 shifts to a positive effect in the period 2005 to 2015.

Our work makes two main contributions to this literature. First, we propose a novel technology life cycle perspective on the analysis of labor market adjustments in response to automation. Much previous research differentiates the short-term effects of automation technologies based on arbitrary time periods which encompass several technological breakthroughs. We explore the shorter-term dynamics defined by the specific life cycle in each of the four groups of automation technologies: robots, CT, IT, and SDB. This lens allows for a more nuanced understanding of how labor markets adjust to technological advancements within distinct phases of technology development.

Second, we contribute to the literature by investigating how the impacts of automation technologies on labor markets vary among regions with different initial levels of productivity and industry specializations. Although Foster-McGregor et al. (2021) highlight the influence of a country's sectoral structure on its exposure to automation, our findings suggest that the impact on the labor market differs more significantly between technological breakthroughs than between regional characteristics. This highlights the importance of the technology life cycle for shaping labor market outcomes, underscoring the need to consider the specific stages of technology development when assessing the effects of automation.

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

2 Data

2.1 Sample

We analyze the impact of technology exposure on labor market outcomes across 163 NUTS-2 regions from 12 European countries over the period 1995 to 2017. The 12 countries included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Spain, and Sweden.[4]

2.2 Data sources and variables

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

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

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

Exposure to automation technologies. We consider four automation technologies:

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

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

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

Based on the available data, we consider computer software (4a) and database (4b) as a single technology.

We employ the number of robots (i.e. robot stock) in use in each sector at the country level using the 2019 Release of the IFR data (for a comprehensive review see Jurkat et al. (2022). Robots are present in three out of six sectors: Industry (B-E), Construction (F),

[4] We opted to 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 identification of these cycles towards the subset of countries with data available up to 1995.

and Non-Market Services (O-U).[5] Since approximately 30% of robots are unspecified (i.e. not assigned to a particular sector), we distributed them proportionally across sectors based on sectoral share.[6] Additionally, for some countries (such as the US) where numbers of robots are not available at the sectoral level for certain years, we estimate their number by distributing the total number of robots weighted by the average sectoral share using years with available data.[7]

ICT and SDB data are from the EU-KLEMS database (Release 2021). We capitalize on the fact that this database distinguishes between these technologies which allows us to analyze the stock of communication equipment (i.e. CT), computing equipment (i.e.IT), and computer software and database (i.e. SDB) at the country-industry level. Our measures for these technology stocks are capital stock (in 2015 volumes), derived from national accounts.[8][9] We converted EUKLEMS figures for non-EU national currencies using the nominal exchange rate from EUROSTAT.[10]

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.[11] Second, we consider the potential impact of trade and international competition by controlling for imports

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

[6]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.

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

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

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

[10]This applies to Denmark, Sweden, and the U.S. (the last is used as an instrument).

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

from China recorded in the OECD Trade in Value Added database.[12] Increased trade with emerging countries has been shown to have adverse effects on manufacturing employment (Autor et al. 2013, Dauth et al. 2014, Autor et al. 2015).

Instrumental variable. To address the endogeneity in the relationship between the decision to invest in automation technologies and labor market outcomes, we use data on investment in the U.S. 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).[13] To construct our instrument (described in section 4), we normalize the technology stock using sectoral employment data from 1980, sourced from the OECD Annual Labour Force Statistics (ALFS).[14]

3 Technological Breakthroughs and their Life Cycles

Similar to innovations in other technologies, automation innovations tend to cluster temporally around major breakthroughs (Silverberg and Verspagen 2003) which promote series of incremental innovations leading to the next major advancement.

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

3.1 ICT Breakthroughs: From the Web 1.0 to Big Data and AI

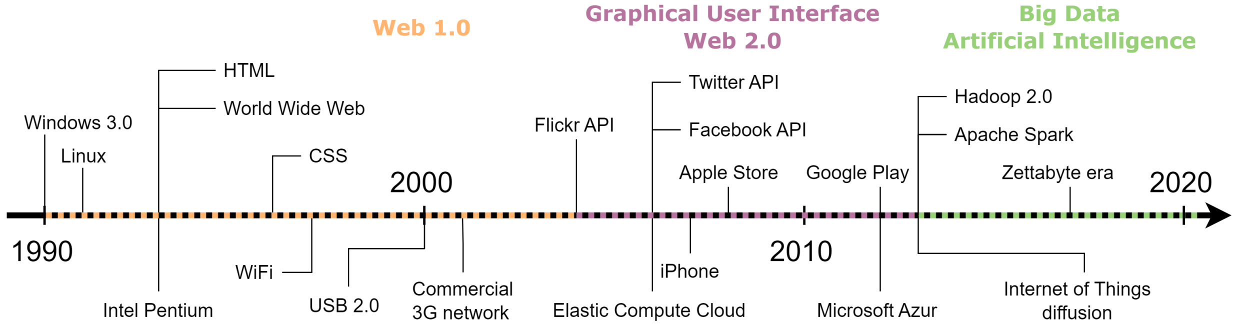
The ICT revolution which began in the early 1970s has been described as “a set of interrelated radical breakthroughs, forming a major constellation of interdependent technologies” (Freeman and Perez 1988, Perez 2010). Nuvolari (2020), identifies four major interdependent technological ICT elements: electronic components, computational power (semiconductors and computers), software, and networking equipment. Radical advancements in these components can lead to significant innovations in ICTs. In particular, the development of

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

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

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

Figure 1: Main digital technology innovations since 1990



Notes: Figure 1 presents the main digital technology innovations since 1990. The 3 digital technological cycles are Web 1.0 (1990 to 2004), graphical user interface and Web 2.0 (2005 to 2012), and big data and AI (from 2013).

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 (GUI) (2006–2012), and Big Data (2013–). We highlight the main features of these three breakthroughs here and provide a more detailed description of the technologies and their components in Appendix E.

Web 1.0 (1990–). During the 1990s, the reduced size and cost of microprocessors significantly increased adoption of personal computers and 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 in 1993 of the World Wide Web (WWW) facilitated adoption of the Internet (CT) by businesses (e.g. e-commerce) and end-users. While software development played a crucial role in disseminating ICT to end-users in the 1990s notably through Windows 3.0, investment in databases was limited.

Graphical User Interface and Cloud Computing (2004–). The second technological breakthrough was marked by the emergence of Web 2.0 technologies in the early 2000s following significant advancements in GUI and Cloud Computing. Previous digital infrastructure developments (i.e. the Internet and mobile communication) spurred the creation of user-friendly devices such as smartphones. This era gave birth to significant network economies (Mansell 2021) and the proliferation of new service applications (e.g. social media, electronic commerce, search engines, data analytics). During this period, also databases 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 (2013–). The third technological breakthrough is characterized by the latest wave of AI which has been driven by increased investments in neural networks and deep learning. This period is characterized by advancements related to machine learning and deep learning algorithms enabled by the growing availability of large data sets or big data, coupled with rapid increases in computational power (facilitated by cloud computing). Significant enhancements to networking and communication technologies have enabled diffusion of the Internet of Things (IoT).[15]

3.2 Robot Breakthroughs: From Industrial Robots to Robotics

Advancements in ICTs, and SDB laid the foundations for the advances in industrial robots.

Industrial Robots (1990–). The development of robotics in the 1990s built on the 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 during the 1990s in communication protocols including the Internet, the WWW, and wireless technologies further expanded control capabilities and spatial movements, leading to the emergence of mobile robots (Grau et al. 2017).

Robotics (2010–). Technologies integral to the evolution of ICT, and SDB enabled a significant shift in robotics. Development of AI technologies in parallel with the emergence of the IoT and sophisticated sensors paved the way to intelligent computing systems. More sophisticated sensors and wireless communication technologies allow complete mobility on manufacturing floors and self-coordination involving swarms of devices (IoT). These radical developments have increased the autonomy of robots, the ability of robots to collaborate with humans, and their precision in various industrial applications (Müller 2022).

In summary, during the period analyzed (1995–2017), we can identify three primary developments (breakthroughs) in ICTs and two main advancements in robotics. In the

[15] The IoT can be defined as a suite of technologies which allows 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.

former case we identify the emergence of Web 1.0 technologies and software alongside cheaper computing costs and rapid advances in user-friendly software (1990–onwards); the emergence of Web 2.0, GUI, simplified data acquisition technologies (e.g. APIs), cloud computing and storage (2005–onwards); and the AI and connectivity (IoT) revolutions (2013–onwards). In the case of industrial robots, we identified enhancements in flexibility, control, and sensing capabilities with the third generation of robots (1990–on), and the introduction of the fourth generation of intelligent robots which built on the developments in AI (2010–on).

3.3 Technology life cycles in ICT and Robots

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

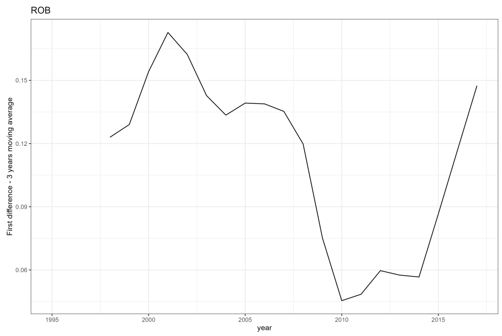
Since our interest is in the life cycles of these technologies and since we lack detailed information on the adoption of specific technologies within each category (robot, IT, CT and SDB), we look at investment patterns aggregated at the European level. For each category of automation technologies, we aggregate investment stock (per 1,000 workers in 1980 at constant prices) across all European countries.[16]

As expected, investment in the four automation technology categories increased annually since 1990 (see Appendix B Figure D.9). To assess the rate of increase, we calculate the first difference in the time series (after applying a 3-year moving average to smooth short-term fluctuations). Figure 2 depicts the changes in investment in robots (2a), CT (2b), IT (2c), and SDB (2d).

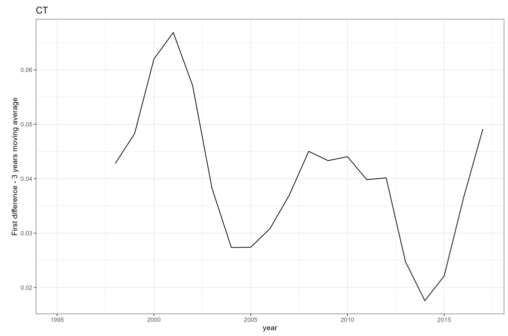
The patterns of investment in ICT and SDB—in the period 1995 to 2017 show three phases of acceleration and deceleration with remarkably similar timing for the three groups of technologies. The Web 1.0 breakthrough in the early 1990s was followed by an investment acceleration phase which persisted to around 2001 and was succeeded by a declining rate of change up to around 2004/5. This period coincided with the emergence of the second breakthrough in our timeframe: GUI and cloud computing after which investment again accelerated up to 2008 to 2011 depending on the technology group and then declining before the next breakthrough (big data and AI) in 2014. The third technology cycle began in 2014 with all three technologies experiencing ongoing increases in investment up to 2017.

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

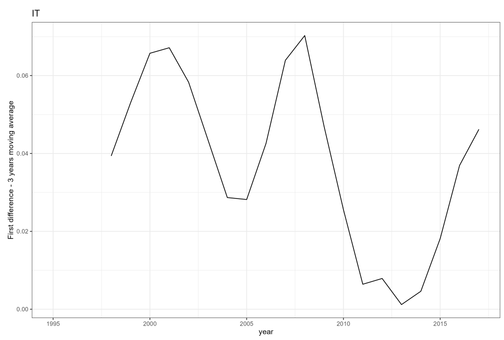
Figure 2: Evolution of technology investment in first difference (3-year moving average)



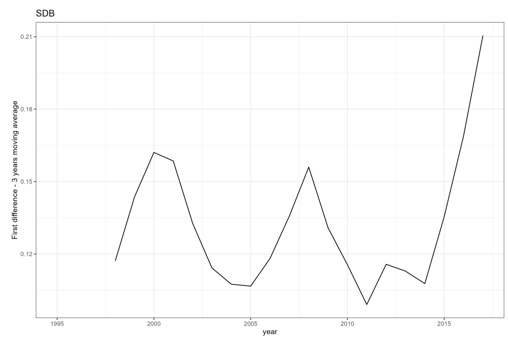
(a) Robots



(b) Communication technologies



(c) Information technologies



(d) Software and database

Notes: Figure 2 depicts the evolution of the first difference in each technology (robots, CT, IT, and SDB) per 1000 workers at the EU level (based on aggregate data for the 12 European countries in the sample). The series were smoothed by taking the 3-year moving average.

Table 1: Phases of the technology life cycles

Cycle	Phase	CT	IT	SDB	Robots
Web 1.0	↑	1995-2001	1995-2001	1995-2000	
	↓	2001-2005	2001-2004	2000-2005	
GUI & Cloud Computing	↑	2005-2011	2004-2008	2005-2008	
	↓	2011-2014	2008-2014	2008-2014	
Big Data - AI	↑	2014-2017	2014-2017	2014-2017	
Industrial Robots	↑				1995-2002
	→				2002-2006
	↓				2006-2013
Robotics	↑				2013-2017

Notes: Table 1 summarizes the years of each phase in the technology life cycles of CT, IT, SDB, and robots based on Figure 2. An ↑ indicates the first phase of rapid diffusion of early vintages of the technology; an ↓ indicates the last phase of slower diffusion of later vintages of the technology; an → indicates stable investment/adoption rates.

Investment in robots shows a distinct trajectory with an acceleration in the first cycle up to 2001, followed by shorter cycles up to 2007 which suggest a prolonged phase of high but diminishing rates of adoption. This period of relatively stable investment growth then transitions into a deceleration phase, lasting until the robotics breakthrough involving big data and AI. This second robot technology lifecycle spanned 2013 to 2017. Table 1 summarizes the technology life cycle phases we used to determine the sub-period for estimating the impact of investment in the four groups of technologies on regional labor markets.

The investment patterns in robots, ICT, and SDB in Europe—which diverge from the cycles in aggregate consumption (see Figure D.8),[17] qualitatively indicate a technology lifecycle characterized by increasing rates of adoption following each breakthrough in the various components of these technologies, and decreasing rates prior to the next breakthrough. While data on the adoption of specific technologies across countries are unavailable, these trends and the discussions in Sections 3.1 and 3.2, imply the presence of distinct phases in the evolution and use of ICT and robots with potentially varying impacts on the labor market.

4 Empirical Specification

Having delineated the technological breakthroughs in ICT and robotics, as well as their respective lifecycles, we next evaluate the impact on regional labor markets in Europe of investment in IT, CT, SDB, and robots. We consider the lifecycle of each technology as an inherent characteristic and thus assume that each region is exposed to every phase in the technology lifecycle. The availability of country level data on ICT and robotics investments allow us to calculate technology exposure (i.e. change in the technology stock) as a shift-share instrument across different phases of the different technological cycles. We estimate our baseline model for labor market adjustments in response to technology exposure throughout these lifecycle phases. Finally, to address identification issues we implement an IV strategy which uses U.S. technology investment as an instrument for European technology investment.

[17] This was also validated by regressing the investment time series for each technology group against a linear time trend and real consumption per 1,000 workers in 1980 aggregated at the European level. The results are depicted in Appendix D Figure D.9. 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.

4.1 Shift-share technology exposure in technological investment phases

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

$$(Exposure_r^{K,EU})_t^{t+h} = \sum_{i \in I} \frac{L_{ri}^{EU}}{L_r^{EU}} \left(\frac{Tech_{i,t+h}^{K,EU}}{L_i^{EU}} - \frac{Tech_{i,t}^{K,EU}}{L_i^{EU}} \right), \tag{1}$$

where L_{ri} is the level of employment in sector i in region r in 1980, L_r is the level of employment in the region in 1980, $Tech_{i,t}^{K,EU}/L_i^{EU}$ is the level of technology stock $K \in \{ROB, IT, CT, SDB\}$ in year t per thousand workers in 1980 in sector i at the country level.[18]

We adjusted our shift-share design to account for the fact that we segment the period from 1995 to 2017 into sub-periods representing the different phases of the technology life cycles.

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

$$(Exposure_r^K)_{1995}^{2017} = \sum_{i \in I} \frac{L_{ri}}{L_r} \left(\frac{Tech_{i,2017}^K}{L_i} - \frac{Tech_{i,t+h'}^K}{L_i} + \frac{Tech_{i,t+h'}^K}{L_i} - \frac{Tech_{i,1995}^K}{L_i} \right).$$

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

$$(Exposure_r^K)_{1995}^{2017} = \underbrace{\sum_{i \in I} \frac{L_{ri}}{L_r} \left(\frac{Tech_{i,2017}^K}{L_i} - \frac{Tech_{i,t+h'}^K}{L_i} \right)}_{\equiv\, Exposure_{r,2}^K} + \underbrace{\sum_{i \in I} \frac{L_{ri}}{L_r} \left(\frac{Tech_{i,t+h'}^K}{L_i} - \frac{Tech_{i,1995}^K}{L_i} \right)}_{\equiv\, Exposure_{r,1}^K},$$

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:

[18] Consequently, our change in exposure is confined to changes in the technology stock. The weights (i.e. sectoral share of employment in the region) remain constant and to avoid endogeneity issues we take 1980 values.

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

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

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

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

In the remaining sections of the paper, the time units for analysis are the phases of investment acceleration and investment deceleration, τ identified in Section 3.3. Since technological cycles do not align perfectly, these phases vary depending on the technology. We denote $\mathcal{T}_K$ as the set of cycle phases for technology K.

4.2 Baseline specification

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

$$y_{r,\tau} = \alpha + \beta \times Exposure_{r,\tau}^K + X'\gamma + u_r, \tag{3}$$

where $y_{r,\tau}$ represents the *annualized* change in the outcome variable for region r during phase τ, $Exposure_{r,\tau}^K$ is the region's exposure to technology K during the same phase, and X includes control variables such as changes in final demand and trade exposure (both calculated using the shift-share method), and exposure to other technologies; u is the error term.

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

Changes in levels of employment and average wage are both calculated as log-changes, allowing the coefficients to be interpreted as percentage changes. Changes in the employment-to-population ratio and the wage share are computed directly, meaning that the coefficients can be interpreted as percentage point changes.

4.3 Identification and IV strategy

The relationship between investment in automation technology and employment and wage outcomes is endogenous. The decision to invest in automation technologies is influenced by the labor cost and availability (Bachmann et al. 2022) including labor market institutional factors (Presidente 2023). Also, some common industry-region level determinants of automation and labor such as labor institutions are not directly observable. Controlling for real consumption (as a proxy for demand shocks) and trade exposure partially but not completely mitigates this issue.

Measuring automation technologies presents several challenges. First, not all robots included in the IFR data are allocated to specific sectors. Second, tangible and intangible capital (such as ICT and software) measuring and accounting methods differ across countries and over time which means that the estimates derived from Equation (3) may be biased. The direction of this bias depends on the prevailing source of endogeneity.

Following the IV used in Acemoglu and Restrepo (2020) and Antón et al. (2022), we use technological investment data for the U.S. a large country undergoing significant automation.[19]

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

$$(Exposure_r^{K,US})_t^{t+h} = \sum_{i \in I} \frac{L_{ri}^{EU}}{L_r^{EU}} \left(\frac{Tech_{i,t+h}^{K,US}}{L_i^{US}} - \frac{Tech_{i,t}^{K,US}}{L_i^{US}} \right), \tag{4}$$

where $Tech_{i,t}^{K,US}/L_i^{US}$ is the level of technology stock K per thousand workers in 1980 in sector i in the US for year t. The years t and $t+h$ correspond to the start and end of the cycle phase, respectively.

By considering changes in technology in the US, we capture exogenous shifts in the technology that might influence its diffusion in a country similar to Europe. We allocate investment proportionally according to the exposure of each region in 1980, based on its sectoral specialization.

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

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

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

where $Exposure_{r,\tau}^{K,EU}$ is the baseline 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 η_c represents the country fixed effect. This fixed effect accounts for between-country differences in technology stocks available for each industry at the national level.

4.4 Regional clusters

To investigate how the effects of automation vary across regions with different characteristics, we categorize them based on productive structure and technological capabilities.

To measure productive structure, we employ a k-means algorithm using regional employment shares in 1980 across three broad sectors—agriculture, industry, and services—as clustering variables.[20] Our preferred specification identifies three distinct groups: agriculture-intensive, industry-intensive, and service-intensive.[21]

To proxy for technological capabilities, we use regional labor productivity in 1980 and classify regions as high or low productivity based on whether their productivity level is above or below the median for the entire sample of regions.[22] Data are from ARDECO.

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

5 Labor Market Impacts of Different Technology Vintages

In this section, we examine the impacts on the labor market of exposure to each technological brakethrough during different phases of their life cycle, for each group of technologies. Our findings are based on the IV estimates presented in Appendix C, Tables C.2 to C.9.[23]

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

[21]In Appendix D, Figure D.1 shows the geographical distribution of regions from our cluster analysis. Figure D.2 presents the goodness-of-fit using 3 metrics. We selected $k = 3$ based on the Bayesian Information Criterion (BIC), which suggests that the optimal number of clusters is between 3 and 5. Appendix B Table B.1 presents the number of regions in each cluster and their within-cluster averages (centers).

[22]Labor productivity is calculated as the ratio of Gross Value Added (GVA) at constant prices to employment (in thousands) in 1980 for each region. For Greece and Ireland where GVA data prior to 1995 are unavailable, thus we use 1995 data for these calculations. Figure D.3 depicts the distribution of regions by productivity level relative to the overall sample of regions.

[23]Tables C.2 to C.5 present the shift-share IV estimation coefficients. Tables C.6 to C.9 present the regional cluster coefficients, estimated separately to highlight the heterogeneity in the relationship between the primary variables. Tables C.10 to C.13 present the results of the ordinary least squares regression.

To investigate whether the cyclical emergence and adoption of breakthroughs in digital automation technologies had short term impacts on the labor market between 1995 and 2017, we compare the results for each breakthrough and their corresponding life cycle phases. We first assess the differences between long- and short-term effects and then investigate patterns in how digital automation technologies have affected employment and wages in European regions throughout the technology life cycles that occurred between 1995 and 2017.

5.1 Short-term *versus* Long-term impacts

Tables C.6 to C.9 show significant short-term positive and negative impacts of all group of digital automation technologies on the regional employment-to-population ratio for several phases of the technology life cycles. However, except for robots which exhibit notably smaller long term effects, the effects do not persist over the long term (Table C.1).[24] Over the whole period 1995-2017, the long-term impacts of ICT and SDB on the employment-to-population ratio are negligible and statistically insignificant (Table C.1 column 3).

For instance, IT exposure has both positive and negative impacts on the regional employment-to-population ratio depending on the cycle phase (Table C.4). Negative effects in the second phase of the first (Web 1.0) and second (GUI and cloud computing) technology life cycles generally outweigh the positive effects observed in the first phase of each of the two cycles.

Fundamentally, over the long term (1995 to 2017), the predominantly negative short-term effects of ICT and SDB exposure on the employment-to-population ratio in European regions are compensated. Various mechanisms potentially mitigate the negative short-term impacts of automation technology investments over time, such as productivity growth, the creation of new tasks and jobs, and product innovations.

The pattern for robots differs in two main respects. First, the short-term impacts of robot exposure are not fully offset in the longer term. Regions investing (1-STD) more in robots experience a 0.07pp annual increase in the employment-to-population ratio which totals 1.54pp for the period 1995-2017 (Table C.1). However, this increase is lower than the sum of the average annualized impacts observed for different robot life cycle phases (Table C.2). Second, for robots, the positive impacts on the employment-to-population ratio dominate the negative impacts which contrasts with the result for ICT. Overall, higher long-term investment in robots results in increased employment, although this general trend conceals diverse short-term effects.

Our analysis of short-term impacts segmented by technology life cycles sheds light on the mixed results in previous studies for the impact of robots on regional employment in

[24] We focus on the employment-to-population ratio to capture the impact of technology investments on population changes including those due to migration.

European countries. Taken together, the effect on employment of the first two phases of the industrial robots life cycle (1995-2002 and 2002-2006) is negative, which is in line with the findings in Antón et al. (2022) of a negative effect for 1995-2005 but a positive effect in the period 2005 to 2015. Our results suggest that the differences related to previous findings may be attributable to the specific technology phases analyzed.

The long-term impact of IT and SDB on average regional wages in the period 1995 to 2017 is minimal and not statistically significant (Table C.1). In contrast to the employment-to-population ratio, this lack of significance is consistent across most short-term periods with notable impacts on wages observed only for the Web 1.0 life cycles which are characterized by widespread adoption of personal computers promoted by user-friendly software (Tables C.4 and C.5).

The impact of CT on wages differs from the impact of IT and SDB. The positive effect of CT on average wages is limited to the Web 1.0 life cycle and shows a substantial annual increase. Regions investing 1-STD more in CT during this period experienced wage increases of 0.24% and 0.99% which were sustained over the long term (Table C.1).

Also in the case of wages, robots show a unique pattern compared to ICT and SDB. The long-term impact of robots on wages is both significant and negative (Table C.1). Regions investing 1-STD more than average in robots experienced an annual wage decrease of about -0.26% or -5.72% over the entire period. However, this long-term impact is less than the sum of the short-term impacts observed between 1995 and 2006 which are attributable to the positive effects noted in the second and more recent technology life cycle (Table C.2).

5.2 Regularities across technology life cycles

The results in Tables C.2 to C.9 highlight four findings related to the influence of the technology life cycle on the impact of automation on regional labor markets.

First, the impact of exposure to automation technologies on the employment-to-population ratio varies among different technological breakthroughs within the same group. Within the same group (e.g. Web 1.0 vs Web 2.0 for IT) the type of technology has a distinct effect. This suggests that combining several technological breakthroughs in a single estimation could yield results that amalgamate these diverse and potentially contrasting effects.

Second, focusing on the second technology life cycle (GUI and cloud computing) which is captured the most accurately by our data,[25] we find that the negative short-term impacts on the employment-to-population ratio are observed predominantly in the later phases. This life cycle combines enhanced flexible computational capacity (cloud computing) with tech-

[25]We do not know when the first cycle starts and when the third cycle ends.

nologies that enable improved coordination and division of labor along the value chain (Web 2.0 and GUI). Our results suggest that in the early phase of rapid technology adoption, employment levels in firms in exposed regions tend to remain stable (Domini et al. 2021), leading to an increase in the employment-to-population ratio. However, in the second phase, when late adopters use more mature technology, investment replaces labor and results in reduced demand for labor. Alternatively, the decrease in the employment-to-population ratio in the second phase may be due to the ability of early adopters to optimize their technology use and reduce their employees. In both cases, in the short term potential increased sales or the creation of new tasks do not compensate.

Third, the effects of exposure to robots on regional employment differ from exposure to ICT and SDB. WHile early adopters of ICT, SDB, and robots experience an increase in the employment-to-population ratio during the early phase of adoption, in the case of robots, late adopters also benefit from increased sales of the mature technology which then leads to employment growth. The negative impact on employment in the case of robots is observed primarily during the intermediate phase where a labor replacement effect outweighs any compensatory mechanisms.

The contrasting effects of robots compared to ICT and SDB suggest that firms take different approaches to the integration of these technologies during the different technology life cycle phases. This suggests the need for further investigation at the firm-occupation level. It might be that the integration of ICT and SDB rather than robots in production processes could lead to more rapid worker replacement effects.

Alternatively, it is possible that these differences might be due to regional compensation mechanisms. For example, the adoption of robots by a limited number of firms Deng et al. (2023) might result in market domination to the detriment of non-adopters. This market shift combined with worker displacement in adopting firms and reduced sales in non-adopting firms, could lead to an overall negative impact on employment during the second phase. However, this trend might reverse in the third phase with the inclusion of late adopters who might benefit from enhanced productivity and output.

Given that ICT, SDB, and robots complement one another (as discussed in Appendix E), the varied impacts across their different life cycle phases may also suggest some interplay among these investments, with some technologies replacing or complementing different tasks (Prytkova et al. 2024). Unraveling the mechanisms behind these differences would require the analysis of both regional and firm data.

Fourth, regional differences in industry specialization and initial productivity affect the results driven by the variations in technology life cycles only marginally. The automation technology vintage and life cycle phase are more relevant than sectoral and productivity differences among regions for explaining the effects on employment of exposure to automation technologies. This argument is based on a comparison among regions with varying initial levels of sector specialization and labor productivity (measured in 1980) across different phases.[26] Tables C.6-C.9 report the impact of technology investment on employment-to-population ratio and average wage which we observe is largely consistent across regions with different initial sector specializations and/or different labor productivity levels (in the case of robots in particular).[27] An exception to this pattern is IT investment, where the most significant impacts on the employment-to-population ratio are observed in highly productive, industry-specialized regions (the European manufacturing core).

6 Conclusion

This paper examined the impact of labor market exposure to different vintages of four groups of digital automation technologies—robots, CT, IT, and SDB—for 163 European regions in 12 European countries. We focused on the short term impacts during each phase of the corresponding technology life cycle of each vintage during the period 1995 to 2017.

We identified the key technological breakthroughs in each technology group and validated them empirically by analyzing investment trends in ICT and robots which identified periods of accelerated and decelerated investment. We examined the effects of these technologies on labor market outcomes including employment levels, the employment-to-population ratio, and the average wage across the two main phases of each technological cycle (acceleration and deceleration). The exposure of regional labor markets to each technology in its respective phases was quantified using a shift-share approach. We also employed an IV strategy, using technology investments in the U.S. to proxy for European investment in these four technology categories.

Our study provides four main results. First, although we observed no effects of ICT and SDB on the employment-to-population ratio over the long-run, over the short term we found evidence of significant positive and (predominantly) negative impacts for each technology life cycle. In practice, this means that although increased demand, spillovers, and emergence of new tasks may compensate for the substitution effect of ICT in the longer term, workers do experience reduced demand in the short run, and particularly in the second phases of the technology life cycles when the technology is more mature. In the case of robots, we found a long-term positive impact on the employment-to-population ratio mitigated by smaller

[26] See section 4 for details of the cluster estimation.

[27] This finding contrasts with the results of Reljic et al. (2023) which includes Eastern European countries and focuses on a shorter period (2011-2018), combining the last phase of the industrial robots life cycle and the first phase of the intelligent robotics life cycle.

negative impacts in one of the life cycle phases. The short term results help to explain the heterogeneous results in the literature on the impact of robots on employment in Europe. The differences found in previous work may be due to the impact of different robot vintages, which we show have different impacts on the labor market.

Second, consistent with prior research, we found that the impact of exposure to different automation technologies (such as robots and ICT) on the labor market varies. Our findings extend this work by showing that the impacts related to different technological breakthrough differ within the same technology group.

Third, we have shown that the impact of technology exposure varies not only by technological breakthrough but also by the phase of the technology life cycle. The differences between phases seem to be consistent across various ICT, particularly when analyzing the technology life cycle that is the most clearly defined in our data (the second cycle). In particular, we show that the first phase of accelerating adoption has a negative impact on the employment-to-population ratio, whereas the second phase of decelerating adoption has a negative impact.

Finally, our analysis indicates that the phase of the technology life cycle plays a more significant role than regional structural differences for determining the impact of labor market exposure to these technologies. This suggests that the timing of technology adoption during its life cycle is crucial for understanding its effects on the labor market.

The main implication of our study is that policy should not ignore the short-term effects of automation since these differ among technologies. While the emergence of new jobs tends to be a long term effect which is accompanied by increased demand due to productivity gains and the introduction of new goods and services, policy interventions should be implemented in the short-term to support workers adversely affected by automation. Specifically, policies should aim to mitigate the short-term negative effects on employment (observed in the case of ICT) and wages (particularly in the case of exposure to robots). Additionally, it is crucial to address the long-term negative consequences on average wages and the potential for increased inequality resulting from robot exposure. Labor market institutions could play an important role in alleviating wage inequality.

Our study has some limitations which suggest directions for future research. The main limitation is lack of data on adoption of specific technologies across countries and regions. While we consider country-specific differences in exposure to technology, our approach assumes uniform adoption of the same technology vintage across all European regions. Also, our analysis does not differentiate between early and late adopting firms within a region.

These limitations underscore the need for more comprehensive comparative studies of countries and regions, using comparable firm-level and employee data. Additionally, considering the varying impacts of these technologies on different worker types, our investigation could be supported by a task-based approach which would provide insights into whether different technology life cycles have significant effects on workforce composition.

References

Abernathy, W. J. and Utterback, J. M. (1978). Patterns of Industrial Innovation. *Technology Review*, 80(7):40–47.

Acemoglu, D., Anderson, G. W., Beede, D. N., Buffington, C., Childress, E. E., Dinlersoz, E., Foster, L. S., Goldschlag, N., Haltiwanger, J. C., Kroff, Z., et al. (2022). Automation and the workforce: A firm-level view from the 2019 annual business survey. NBER Working Paper Series 30659, National Bureau of Economic Research (NBER).

Acemoglu, D., Lelarge, C., and Restrepo, P. (2020). Competing with Robots: Firm-Level Evidence from France. *AEA Papers and Proceedings*, 110:383–88.

Acemoglu, D. and Restrepo, P. (2020). Robots and jobs: Evidence from US Labor Markets. *Journal of Political Economy*, 128(6):2188–2244.

Aghion, P., Antonin, C., and Bunel, S. (2019). Artificial Intelligence, Growth and Employment: The Role of Policy. *Economie et Statistique / Economics and Statistics*, 510-511-51:149–164.

Aghion, P., Antonin, C., Bunel, S., and Jaravel, X. (2022). The Effects of Automation on Labor Demand: A Survey of the Recent Literature. CEPR Discussion Paper 16868, Centre for Economic Policy Research (CEPR).

Andreoni, A., Chang, H. J., and Labrunie, M. (2021). Natura Non Facit Saltus: Challenges and Opportunities for Digital Industrialisation Across Developing Countries. *European Journal of Development Research*, 33(2):330–370.

Antón, J. I., Klenert, D., Fernández-Macías, E., Urzì Brancati, M. C., and Alaveras, G. (2022). The labour market impact of robotisation in Europe. *European Journal of Industrial Relations*, 28(3):317–339.

Autor, D., Chin, C., Salomons, A. M., and Seegmiller, B. (2022). New Frontiers: The Origins and Content of New Work, 1940–2018. NBER Working Paper 30389, National Bureau of Economic Research (NBER).

Autor, D. H. (2015). Why Are There Still So Many Jobs? The History and Future of Workplace Automation. *Journal of Economic Perspectives*, 29(3):3–30.

Autor, D. H., Dorn, D., and Hanson, G. H. (2013). The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review*, 103(6):2121–68.

Autor, D. H., Dorn, D., and Hanson, G. H. (2015). Untangling Trade and Technology: Evidence from Local Labour Markets. *The Economic Journal*, 125(584):621–646.

Autor, D. H., Levy, F., and Murnane, R. J. (2002). Upstairs, Downstairs: Computers and Skills on Two Floors of a Large Bank. *ILR Review*, 55(3):432–447.

Autor, D. H., Levy, F., and Murnane, R. J. (2003). The Skill Content of Recent Technological Change: An Empirical Exploration. *Quarterly Journal of Economics*, 118(4):1279–1333.

Bachmann, R., Gonschor, M., Lewandowski, P., and Madoń, K. (2022). The Impact of Robots on Labour Market Transitions in Europe. IZA Discussion Paper Series 15303, Institute of Labor Economics (IZA).

Barnett, T. J. (2016). The Zettabyte Era Officially Begins (How Much is That?). *Cisco Blogs*. https://blogs.cisco.com/sp/the-zettabyte-era-officially-begins-how-much-is-that.

Baruffaldi, S., Beuzekom, B. V., Dernis, H., Harhoff, D., Rao, N., and Rosenfeld, D. (2020). Identifying and measuring developments in artificial intelligence : Making the impossible possible. OECD Science, Technology and Industry Working Papers 2020/05, Organization for Economic Cooperation and Development (OECD).

Battisti, M., Dustmann, C., and Schönberg, U. (2023). Technological and Organizational Change and the Careers of Workers. *Journal of the European Economic Association*, 21(4):1551–1594.

Blanas, S. (2023). The distinct effects of information technologies and communication technologies on skill demand. *Available at https://ssrn.com/abstract=4061902*.

Bloom, N. and Pierri, N. (2018). Cloud computing is helping smaller, newer firms compete. *Harvard Business Review*. https://hbr.org/2018/08/research-cloud-computing-is-helping-smaller-newer-firms-compete.

Brynjolfsson, E. and McAfee, A. (2014). *The second machine age: Work, progress, and prosperity in a time of brilliant technologies*. W.W. Norton & Company.

Brynjolfsson, E. and Mcafee, A. (2017). Artificial intelligence, for real. *Harvard Business Review*. https://starlab-alliance.com/wp-content/uploads/2017/09/AI-Article.pdf.

Calvino, F., Samek, L., Squicciarini, M., and Morris, C. (2022). Identifying and characterising ai adopters: A novel approach based on big data. OECD Science, Technology and Industry Working Papers 2022/06, Organization for Economic Cooperation and Development (OECD).

Cao, C., Liu, F., Tan, H., Song, D., Shu, W., Li, W., Zhou, Y., Bo, X., and Xie, Z. (2018). Deep Learning and Its Applications in Biomedicine. *Genomics, Proteomics & Bioinformatics*, 16(1):17–32.

Chiacchio, F., Petropoulos, G., and Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. Bruegel Working Paper 2018/02, Bruegel.

Ciarli, T., Kenney, M., Massini, S., and Piscitello, L. (2021). Digital technologies, innovation, and skills: Emerging trajectories and challenges. *Research Policy*, 50(7):104289.

Cockburn, I. M., Henderson, R., and Stern, S. (2018). The impact of artificial intelligence on innovation: An exploratory analysis. In *The economics of artificial intelligence: An agenda*, pages 115–146. University of Chicago Press.

Crook, I. (2018). When did mobile apps become so popular? *AppInstitute*. https://appinstitute.com/mobile-apps-become-popular/.

Dauth, W., Findeisen, S., and Suedekum, J. (2014). The rise of the East and the Far East: German labor markets and trade integration. *Journal of the European Economic Association*, 12(6):1643–1675.

Dauth, W., Findeisen, S., Suedekum, J., and Woessner, N. (2021). The Adjustment of Labor Markets to Robots. *Journal of the European Economic Association*, 19(6):3104–3153.

David, P. A. (1985). Clio and the Economics of QWERTY. *The American Economic Review*, 75(2):332–337.

Deng, L., Plümpe, V., and Stegmaier, J. (2023). Robot adoption at German plants. *Journal of Economics and Statistics*.

DeStefano, T., Kneller, R., and Timmis, J. (2023). Cloud Computing and Firm Growth. *Review of Economics and Statistics*, pages 1–47.

Domini, G., Grazzi, M., Moschella, D., and Treibich, T. (2021). Threats and opportunities in the digital era: Automation spikes and employment dynamics. *Research Policy*, 50(7):104137.

Etro, F. (2009). The Economic Impact of Cloud Computing on Business Creation, Employment and Output in Europe: An application of the Endogenous Market Structures Approach to a GPT innovation. *Review of Business and Economics*, 54(2):179–208.

EUKLEMS&INTANProd (2021). The EUKLEMS & INTANProd productivity database: Methods and data description. Deliverable D2.1, LUISS Lab of European Economics, LUISS University.

Foote, K. D. (2021). A brief history of cloud computing. *Datadiversity*. https://www.dataversity.net/brief-history-cloud-computing/.

Foster-McGregor, N., Önder Nomaler, and Verspagen, B. (2021). Job Automation Risk, Economic Structure and Trade: a European Perspective. *Research Policy*, 50(7):104269.

Freeman, C. and Louçã, F. (2001). *As time goes by: from the industrial revolutions to the information revolution*. Oxford University Press.

Freeman, C. and Perez, C. (1988). Structural crisis of adjustment, business cycles and investment behaviour. In Dosi, G., Freeman, C., Nelson, R., Gerald, S., and Soete, L., editors, *Technical change and economic theory*, pages 38–66. Pinter Publishers, London, N.Y.

Frey, C. B. and Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114:254–280.

Gasparetto, A., Scalera, L., Gasparetto, A., and Scalera, L. (2019). A Brief History of Industrial Robotics in the 20th Century. *Advances in Historical Studies*, 8(1):24–35.

Geroski, P. (2000). Models of technology diffusion. *Research Policy*, 29(4-5):603–625.

Goos, M., Manning, A., and Salomons, A. (2014). Explaining Job Polarization: Routine-Biased Technological Change and Offshoring. *The American Economic Review*, 104(8):2509–2526.

Graetz, G. and Michaels, G. (2018). Robots at Work. *Review of Economics and Statistics*, 100(5):753–768.

Grau, A., Indri, M., Bello, L. L., and Sauter, T. (2017). Industrial robotics in factory automation: From the early stage to the internet of things. In *IECON 2017 - 43rd Annual Conference of the IEEE Industrial Electronics Society*, pages 6159–6164.

Gregory, T., Salomons, A., and Zierahn, U. (2022). Racing with or Against the Machine? Evidence on the Role of Trade in Europe. *Journal of the European Economic Association*, 20(2):869–906.

Gupta, D. and Rani, R. (2019). A study of big data evolution and research challenges. *Journal of information science*, 45(3):322–340.

IBMCloudEducation (2021). Hadoop vs. spark: What's the difference? *IBM Blog*. https://www.ibm.com/blog/hadoop-vs-spark/.

Jestl, S. (2024). Industrial robots, and information and communication technology: the employment effects in EU labour markets. *Regional Studies*, 0(0):1–18.

Jurkat, A., Klump, R., and Schneider, F. (2022). Tracking the rise of robots: The IFR database. *Jahrbücher für Nationalökonomie und Statistik*, 242(5-6):669–689.

Khanna, A. and Kaur, S. (2020). Internet of Things (IoT), Applications and Challenges: A Comprehensive Review. *Wireless Personal Communications*, 114:1687–1762.

Kim, D. J., Yue, K.-B., Hall, S. P., and Gates, T. (2009). Global diffusion of the internet XV: Web 2.0 technologies, principles, and applications: A conceptual framework from technology push and demand pull perspective. *Communications of the Association for Information Systems*, 24(1):38.

Lane, K. (2019). Intro to APIs: History of APIs. *The Postman Blog*. https://blog.postman.com/intro-to-apis-history-of-apis/.

Langlois, R. N. (2003). Cognitive comparative advantage and the organization of work: Lessons from Herbert Simon's vision of the future. *Journal of Economic Psychology*, 24(2):167–187.

Lee, I. (2017). Big data: Dimensions, evolution, impacts, and challenges. *Business Horizons*, 60(3):293–303.

Lewis, P. (2020). Developing Technician Skills for Innovative Industries: Theory, Evidence from the UK Life Sciences Industry, and Policy Implications. *British Journal of Industrial Relations*, 58(3):617–643.

Malerba, F., Nelson, R., Orsenigo, L., and Winter, S. G. (1999). History-friendly' models of industry evolution: the computer industry. *Indsutrial and Corporate Change*, 8(1):3–40.

Mansell, R. (2021). Adjusting to the digital: Societal outcomes and consequences. *Research Policy*, 50(9):104296.

Mowery, D. C. and Simcoe, T. (2002). Is the internet a US invention?—an economic and technological history of computer networking. *Research Policy*, 31(8):1369–1387.

Müller, C. (2022). World Robotics 2022 – Industrial Robots. Ifr statistical department, vdma services gmbh, International Federation of Robotics (IFR), Frankfurt am Main.

Nuvolari, A. (2020). The ICT Revolution in Historical Perspective. GROWINPro Working Paper 3/2020, European Union Horizon 2020.

O'Reilly, T. (2007). What is Web 2.0: Design Patterns and Business Models for the Next Generation of Software. MPRA Paper No. 4578, Munich Personal RePEc Archive (MPRA).

Perez, C. (2010). Technological revolutions and techno-economic paradigms. *Cambridge journal of economics*, 34(1):185–202.

Petit, F., Jaccoud, F., and Ciarli, T. (2022). Heterogeneous Adjustments of Labor Markets to Automation Technologies. CESifo Working Paper 10237, CESifo.

Pilat, D. (2005). The ICT Productivity Paradox: Insights from Micro Data. *OECD economic studies*, 2004(1):37–65.

Presidente, G. (2023). Institutions, Holdup, and Automation. *Industrial and Corporate Change*, 32(4):831–847.

Prytkova, E., Petit, F., Li, D., Chaturvedi, S., and Ciarli, T. (2024). The Employment Impact of Emerging Digital Technologies. Working Paper.

Reljic, J., Cirillo, V., and Guarascio, D. (2023). Regimes of robotization in Europe. *Economics Letters*, 232:111320.

Savona, M., Ciarli, T., Steinmueller, E., and Vannuccini, S. (2022). The Design of Digital Automation Technologies: Implications for the Future of Work. *EconPol Forum*, 23(05):4–10.

Silverberg, G. and Verspagen, B. (2003). Breaking the waves: a Poisson regression approach to Schumpeterian clustering of basic innovations. *Cambridge Journal of Economics*, 27(5):671–693.

Simon, H. A. (1960). The Corporation: Will It Be Managed by Machines? In Anshen, M. and Bach, G., editors, *Management and the Corporations, 1985*, pages 17–55. McGraw-Hill, New York.

Tushman, M. L. and Anderson, P. (1986). Technological Discontinuities and Organizational Environments. *Administrative Science Quarterly*, 31(3):439.

Vannuccini, S. and Prytkova, E. (2023). Artificial intelligence's new clothes? a system technology perspective. *Journal of Information Technology*, 0(0):02683962231197824.

Vivarelli, M. (1995). *The Economics of Technology and Employment: Theory and Empirical Evidence.* Edward Elgar Publishing.

Vona, F. and Consoli, D. (2015). Innovation and skill dynamics: a life-cycle approach. *Industrial and Corporate Change*, 24(6):1393–1415.

Zolas, N. J., Kroff, Z., Brynjolfsson, E., McElheran, K. S., Beede, D., Buffington, C., Goldschlag, N., Foster, L., and Dinlersoz, E. (2021). Advanced Technologies Adoption and Use by U.S. Firms: Evidence from the Annual Business Survey. NBER Working Paper Series 28290, National Bureau of Economic Research (NBER).

Zuboff, S. (1988). *In the Age of the Smart Machine: The Future of Work and Power.* Basic Books, New York.

Appendices

A Data

This appendix presents further details on the data as well as summary statistics. We provide additional tables and figures about the classification of sectors used in the analysis and the stocks and prices of technologies.

A.1 Sector aggregation

We consider six sectors as the result of the aggregation and compatibilization between NACE Rev. 1.1 and Rev. 2. This section relies on the methodology adopted in Petit et al. (2022). Agriculture (A) corresponds to activities that relate to agriculture, forestry, and fishing. Industry (B-E) refers to manufacturing, mining and quarrying, utilities; except Construction (F) which is a sector in itself. Market Services (G-J) encompass service activities such as wholesale and retail trade, accommodation and food service activities, transportation and storage, along with information and communication. Financial & Business Services (K-N) correspond to financial and insurance activities; real estate activities; professional, scientific, technical, administration and support service activities. Lastly, Non-Market Services (O-U) regroup all other services such as public administration and defense, education, human health and social work activities; and any other service activities.

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

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

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

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

Table A.2: Overview of NACE classifications

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

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

B Descriptive Statistics

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

Table B.1: Clusters and K-means

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

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

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

Table B.2: Summary statistics of the change in the long run (1995–2017)

Variable	Mean	SD	Min	Q1	Q2	Q3	Max	N
Emp	0.9	0.6	-0.2	0.5	0.8	1.1	3.2	163
Emp-to-pop	0.2	0.1	-0.3	0.1	0.2	0.3	0.6	163
Wage	0.7	0.6	-0.5	0.4	0.6	1.0	3.0	162
ROB	2.1	1.7	0.0	1.0	1.7	2.8	7.1	163
CT	1.0	0.6	0.2	0.6	0.7	1.0	3.3	163
IT	0.9	0.7	0.1	0.4	0.6	0.9	2.9	163
SDB	3.0	2.0	0.2	1.3	2.5	4.2	9.6	163
Imports	2.0	0.9	0.4	1.3	1.9	2.7	3.9	163
Final demand	5.1	7.1	-8.0	0.0	5.1	8.3	42.0	163

Notes: This table shows the summary statistics of the change in the outcome, independent, and control variables for the 163 NUTS-2 regions between 1995 and 2017. Outcomes variables are employment, employment-to-population ratio (Emp-to-pop. ratio)—measured as the total number of employed persons aged 15-64 over the total population—, average yearly wage per worker (Wage) in thousands euros of 2015—calculated as the ratio between total labor compensation and the level of employment, and Wage share—measured as total compensation over gross value added. 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 technology (CT), information technology (IT), and software and database (SDB). Data are from the IFR for robots and EU-KLEMS for the rest. Control variables are imports—measured as imports from China using the OECD Trade in Value Added database—and final demand—measured as the real consumption index from the Inter-Country Input-Output database.

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

Table B.3: Summary statistics for technology stock by region specialization in 1995

Tech	Cluster	Mean	SD	Min	Q1	Q2	Q3	Max	N
ROB	Agriculture intensive	0.58	0.49	0.00	0.30	0.45	0.66	1.86	47
	Industry intensive	1.02	0.68	0.00	0.51	0.86	1.44	2.48	72
	Service intensive	0.56	0.52	0.00	0.17	0.50	0.77	1.86	44
CT	Agriculture intensive	1.16	2.28	0.06	0.32	0.43	0.75	11.55	47
	Industry intensive	1.32	2.60	0.06	0.38	0.60	0.80	11.89	72
	Service intensive	1.39	2.47	0.07	0.33	0.72	0.98	11.97	44
IT	Agriculture intensive	0.44	1.11	0.05	0.14	0.25	0.35	7.71	47
	Industry intensive	0.70	1.60	0.05	0.17	0.35	0.45	8.37	72
	Service intensive	0.62	1.54	0.04	0.17	0.36	0.51	10.45	44
SDB	Agriculture intensive	2.26	4.78	0.04	0.74	0.93	2.21	24.94	47
	Industry intensive	2.86	5.69	0.06	0.78	1.03	1.99	27.60	72
	Service intensive	2.76	6.38	0.08	0.92	1.07	1.91	37.47	44

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

Table B.4: Summary statistics for technology stock by productivity level in 1995

Tech	Productivity	Mean	SD	Min	Q1	Q2	Q3	Max	N
ROB	High Productivity	0.93	0.65	0.00	0.40	0.77	1.34	2.48	82
	Low Productivity	0.61	0.57	0.00	0.18	0.45	0.79	2.29	81
CT	High Productivity	1.07	1.90	0.06	0.34	0.59	0.77	11.97	82
	Low Productivity	1.52	2.92	0.06	0.31	0.58	0.87	11.89	81
IT	High Productivity	0.89	2.00	0.05	0.16	0.38	0.53	10.45	82
	Low Productivity	0.32	0.26	0.04	0.15	0.28	0.35	1.17	81
SDB	High Productivity	2.46	4.79	0.05	0.81	1.65	2.23	37.47	82
	Low Productivity	2.86	6.36	0.04	0.75	0.96	1.73	27.60	81

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

C Regressions

Table C.1: Annualized long-run adjustments to technology exposure. 1995-2017.

	IV and OLS Regression - Dep. var.:					
	Employment		Emp-to-pop ratio		Average wage	
	2SLS	OLS	2SLS	OLS	2SLS	OLS
Robot Exposure	0.22^{***}	0.23^{***}	0.07^{***}	0.07^{***}	-0.26^{***}	-0.18^{**}
	(0.08)	(0.07)	(0.02)	(0.02)	(0.08)	(0.07)
CT Exposure	-0.10^{**}	-0.10^{**}	0.00	0.00	0.23^{***}	0.20^{***}
	(0.05)	(0.05)	(0.01)	(0.01)	(0.05)	(0.05)
IT Exposure	0.09^{*}	0.12^{**}	0.01	0.02	-0.03	-0.02
	(0.05)	(0.05)	(0.01)	(0.01)	(0.05)	(0.06)
Software/Database Exposure	0.07	0.07	-0.01	-0.01	0.09	0.09
	(0.06)	(0.06)	(0.01)	(0.01)	(0.06)	(0.06)
Final demand	Yes	Yes	Yes	Yes	Yes	Yes
Trade	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.24	0.26	0.25	0.25	0.24	0.18
Adj. R^2	0.21	0.23	0.22	0.23	0.21	0.15
Num. obs.	163	163	163	163	162	162

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated OLS and IV-regressions of labor outcomes on technology K exposure (where K is Robot, IT, CT, and Software/Database respectively). The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the period 1995-2017. The technology exposure to K is calculated using the shift-share method and subsequently standardized. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to technology K during the period. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies.

Table C.2: Adjustments to robot exposure during robot investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable			
	Industrial Robots			Robotics
	1995-2002	2002-2006	2006-2013	2013-2017
[A] **Employment** (in percent)				
ROB Exposure	0.13	-0.56^{***}	0.55^{***}	0.09
	(0.13)	(0.09)	(0.09)	(0.08)
[B] **Employment-to-population ratio** (in pp.)				
ROB Exposure	0.19^{***}	-0.14^{***}	0.36^{***}	-0.05^{*}
	(0.04)	(0.03)	(0.04)	(0.03)
[C] **Average wage** (in percent)				
ROB Exposure	-1.01^{***}	-0.55^{***}	0.05	0.41^{***}
	(0.15)	(0.10)	(0.09)	(0.08)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on robot exposure over the phases of the robot's life cycle. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the robot's life cycle. Robot exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to robot in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies.

Table C.3: Adjustments to communication technology exposure during CT investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2005	2005-2011	2011-2014	2014-2017
[A] **Employment** (in percent)					
CT Exposure	-0.33^{***}	-0.22^{**}	-0.09	-0.39^{***}	-0.00
	(0.10)	(0.09)	(0.08)	(0.10)	(0.08)
[B] **Employment-to-population ratio** (in pp.)					
CT Exposure	-0.06	-0.00	-0.01	-0.17^{***}	-0.02
	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)
[C] **Average wage** (in percent)					
CT Exposure	0.24^{**}	0.99^{***}	-0.08	0.11	-0.07
	(0.11)	(0.11)	(0.08)	(0.12)	(0.08)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on CT exposure over the phases of the CT's life cycle. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the CT's life cycle. CT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to CT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies.

Table C.4: Adjustments to information technology exposure during IT investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2004	2004-2008	2008-2014	2014-2017
[A] Employment (in percent)					
IT Exposure	0.12	-0.44^{***}	0.11	-0.23^{**}	-0.16^{*}
	(0.11)	(0.10)	(0.07)	(0.10)	(0.09)
[B] Employment-to-population ratio (in pp.)					
IT Exposure	0.08^{*}	-0.14^{***}	0.07^{***}	-0.13^{***}	-0.08^{**}
	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)
[C] Average wage (in percent)					
IT Exposure	0.04	-0.01	0.10	0.11	-0.12
	(0.12)	(0.13)	(0.10)	(0.09)	(0.10)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on IT exposure over the phases of the IT's life cycle. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the IT's life cycle. IT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to IT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies.

Table C.5: Adjustments to software/database exposure during SDB investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2000	2000-2005	2005-2008	2008-2014	2014-2017
[A] Employment (in percent)					
SDB Exposure	-0.09	0.12	0.10^{*}	0.01	0.25^{**}
	(0.12)	(0.07)	(0.06)	(0.14)	(0.10)
[B] Employment-to-population ratio (in pp.)					
SDB Exposure	-0.01	0.02	0.06^{**}	-0.10^{**}	0.07^{**}
	(0.04)	(0.03)	(0.02)	(0.05)	(0.03)
[C] Average wage (in percent)					
SDB Exposure	-0.23^{*}	-0.23^{***}	0.07	0.12	0.14
	(0.14)	(0.08)	(0.11)	(0.12)	(0.10)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on SDB exposure over the phases of the SDB's life cycle. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the SDB's life cycle. SDB exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to SDB in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies.

Table C.6: Adjustments to robot exposure during robot investment cycles by cluster

	IV regression - Dep. var.: annualized change in the outcome variable			
	Industrial Robots			Robotics
	1995-2002	2002-2006	2006-2013	2013-2017
[A] **Employment** (in percent)				
ROB Exposure	0.13	-0.56^{***}	0.55^{***}	0.09
	(0.13)	(0.09)	(0.09)	(0.08)
in Agriculture	0.07	-0.57^{***}	0.73^{***}	0.22^{*}
	(0.25)	(0.20)	(0.19)	(0.13)
in Industry	0.28^{**}	-0.45^{***}	0.53^{***}	-0.03
	(0.14)	(0.11)	(0.13)	(0.10)
in Service	-0.08	-0.71^{***}	0.37^{**}	0.14
	(0.35)	(0.21)	(0.18)	(0.24)
in Low	0.25	-0.55^{**}	0.52^{***}	-0.12
	(0.21)	(0.22)	(0.17)	(0.16)
in High	0.16	-0.73^{***}	0.54^{***}	0.07
	(0.18)	(0.10)	(0.09)	(0.09)
[B] **Employment-to-population ratio** (in pp.)				
ROB Exposure	0.19^{***}	-0.14^{***}	0.36^{***}	-0.05^{*}
	(0.04)	(0.03)	(0.04)	(0.03)
in Agriculture	0.18^{***}	-0.11	0.37^{***}	-0.01
	(0.06)	(0.07)	(0.07)	(0.04)
in Industry	0.19^{***}	-0.13^{***}	0.37^{***}	-0.10^{**}
	(0.05)	(0.03)	(0.07)	(0.04)
in Service	0.21	-0.20^{**}	0.33^{***}	-0.01
	(0.13)	(0.09)	(0.10)	(0.05)
in Low	0.26^{***}	-0.18^{**}	0.36^{***}	-0.17^{***}
	(0.06)	(0.08)	(0.08)	(0.04)
in High	0.16^{**}	-0.18^{***}	0.35^{***}	-0.04
	(0.06)	(0.04)	(0.05)	(0.03)
[C] **Average wage** (in percent)				
ROB Exposure	-1.01^{***}	-0.55^{***}	0.05	0.41^{***}
	(0.15)	(0.10)	(0.09)	(0.08)
in Agriculture	-1.37^{***}	-0.59^{***}	-0.21	0.26^{*}
	(0.31)	(0.17)	(0.22)	(0.15)
in Industry	-0.54^{***}	-0.64^{***}	0.16	0.48^{***}
	(0.16)	(0.12)	(0.11)	(0.06)
in Service	-1.56^{***}	-0.61^{*}	0.03	0.41^{*}
	(0.41)	(0.31)	(0.22)	(0.22)
in Low	-1.15^{***}	-0.65^{**}	0.01	0.68^{***}
	(0.24)	(0.28)	(0.17)	(0.14)
in High	-0.83^{***}	-0.08	0.07	0.48^{***}
	(0.20)	(0.11)	(0.10)	(0.08)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on robot exposure over the phases of the robot's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the robot's life cycle. Robot exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to robot in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.7: Adjustments to communication technology exposure during CT investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2005	2005-2011	2011-2014	2014-2017
[A] Employment (in percent)					
CT Exposure	-0.33^{***}	-0.22^{**}	-0.09	-0.39^{***}	-0.00
	(0.10)	(0.09)	(0.08)	(0.10)	(0.08)
in Agriculture	-0.54^{***}	0.05	-0.03	-0.68^{***}	-0.04
	(0.19)	(0.22)	(0.22)	(0.18)	(0.12)
in Industry	-0.06	-0.12	0.09	-0.18	0.12
	(0.12)	(0.12)	(0.16)	(0.12)	(0.12)
in Service	-0.58^{**}	-0.32^{*}	-0.21^{*}	-0.36	-0.06
	(0.22)	(0.18)	(0.12)	(0.23)	(0.17)
in Low	-0.27^{*}	-0.39^{***}	-0.15	-1.00^{***}	0.66^{***}
	(0.16)	(0.12)	(0.11)	(0.23)	(0.18)
in High	-0.26^{*}	0.01	-0.10	0.01	-0.27^{***}
	(0.14)	(0.16)	(0.16)	(0.09)	(0.09)
[B] Employment-to-population ratio (in pp.)					
CT Exposure	-0.06	-0.00	-0.01	-0.17^{***}	-0.02
	(0.04)	(0.04)	(0.05)	(0.03)	(0.03)
in Agriculture	-0.06	0.04	0.05	-0.20^{***}	0.02
	(0.05)	(0.09)	(0.10)	(0.05)	(0.04)
in Industry	-0.02	-0.01	0.14	-0.11^{***}	0.02
	(0.05)	(0.04)	(0.10)	(0.04)	(0.05)
in Service	-0.15	-0.00	-0.03	-0.18^{***}	-0.06
	(0.09)	(0.09)	(0.08)	(0.06)	(0.05)
in Low	0.02	-0.04	-0.03	-0.33^{***}	0.24^{***}
	(0.05)	(0.05)	(0.07)	(0.07)	(0.06)
in High	-0.07	0.05	-0.04	-0.07^{**}	-0.10^{***}
	(0.05)	(0.07)	(0.09)	(0.03)	(0.03)
[C] Average wage (in percent)					
CT Exposure	0.24^{**}	0.99^{***}	-0.08	0.11	-0.07
	(0.11)	(0.11)	(0.08)	(0.12)	(0.08)
in Agriculture	0.31	0.90^{***}	0.16	-0.00	0.09
	(0.21)	(0.24)	(0.22)	(0.34)	(0.13)
in Industry	0.32^{**}	1.20^{***}	-0.28^{**}	0.11	-0.08
	(0.13)	(0.13)	(0.11)	(0.16)	(0.10)
in Service	0.24	0.44^{*}	-0.28	-0.03	-0.45^{**}
	(0.26)	(0.26)	(0.18)	(0.21)	(0.17)
in Low	0.21	1.08^{***}	-0.11	0.18	-0.89^{***}
	(0.17)	(0.17)	(0.13)	(0.23)	(0.20)
in High	0.19	0.23	-0.08	-0.14	0.06
	(0.14)	(0.14)	(0.12)	(0.17)	(0.10)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on CT exposure over the phases of the CT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the CT's life cycle. CT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to CT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.8: Adjustments to information technology exposure during IT investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2004	2004-2008	2008-2014	2014-2017
[A] **Employment** (in percent)					
IT Exposure	0.12	-0.44^{***}	0.11	-0.23^{**}	-0.16^{*}
	(0.11)	(0.10)	(0.07)	(0.10)	(0.09)
in Agriculture	0.22	-0.32	0.28^{*}	-0.08	-0.40^{**}
	(0.25)	(0.25)	(0.16)	(0.18)	(0.17)
in Industry	0.16	-0.32^{**}	0.16^{*}	-0.20	-0.11
	(0.11)	(0.13)	(0.09)	(0.12)	(0.11)
in Service	-0.20	-0.79^{***}	-0.28^{**}	-0.12	-0.12
	(0.26)	(0.25)	(0.13)	(0.19)	(0.24)
in Low	-0.36	-0.49^{**}	-0.11	0.09	-0.96^{***}
	(0.24)	(0.22)	(0.13)	(0.26)	(0.30)
in High	0.31^{**}	-0.27^{**}	0.31^{***}	-0.45^{***}	0.05
	(0.12)	(0.10)	(0.07)	(0.08)	(0.09)
[B] **Employment-to-population ratio** (in pp.)					
IT Exposure	0.08^{*}	-0.14^{***}	0.07^{***}	-0.13^{***}	-0.08^{**}
	(0.04)	(0.05)	(0.03)	(0.03)	(0.03)
in Agriculture	0.01	-0.09	0.07	-0.10^{*}	-0.22^{***}
	(0.07)	(0.09)	(0.06)	(0.05)	(0.06)
in Industry	0.06	-0.14^{***}	0.10^{***}	-0.12^{**}	-0.08^{*}
	(0.05)	(0.04)	(0.03)	(0.05)	(0.04)
in Service	0.04	-0.28^{**}	-0.06	-0.10	-0.05
	(0.11)	(0.13)	(0.05)	(0.07)	(0.07)
in Low	-0.03	-0.02	0.05	0.02	-0.60^{***}
	(0.08)	(0.09)	(0.05)	(0.08)	(0.09)
in High	0.11^{**}	-0.13^{**}	0.09^{***}	-0.17^{***}	0.00
	(0.05)	(0.05)	(0.03)	(0.03)	(0.03)
[C] **Average wage** (in percent)					
IT Exposure	0.04	-0.01	0.10	0.11	-0.12
	(0.12)	(0.13)	(0.10)	(0.09)	(0.10)
in Agriculture	-0.05	0.23	0.21	0.15	0.17
	(0.28)	(0.34)	(0.18)	(0.22)	(0.19)
in Industry	0.34^{**}	-0.20	0.17	0.02	-0.08
	(0.13)	(0.14)	(0.15)	(0.11)	(0.10)
in Service	-0.16	-0.08	-0.06	0.15	-0.38
	(0.30)	(0.31)	(0.27)	(0.17)	(0.23)
in Low	0.28	0.17	-0.08	0.59^{**}	-0.02
	(0.27)	(0.33)	(0.19)	(0.23)	(0.33)
in High	0.08	0.02	0.17^{*}	0.03	-0.09
	(0.13)	(0.08)	(0.09)	(0.09)	(0.10)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on IT exposure over the phases of the IT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the IT's life cycle. IT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to IT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.9: Adjustments to software/database exposure during SDB investment cycles

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2000	2000-2005	2005-2008	2008-2014	2014-2017
[A] Employment (in percent)					
SDB Exposure	-0.09	0.12	0.10^{*}	0.01	0.25^{**}
	(0.12)	(0.07)	(0.06)	(0.14)	(0.10)
in Agriculture	0.29	0.08	0.12	-0.17	0.67^{***}
	(0.23)	(0.15)	(0.14)	(0.26)	(0.18)
in Industry	-0.30^{**}	0.04	0.02	-0.36^{*}	0.05
	(0.14)	(0.10)	(0.07)	(0.19)	(0.13)
in Service	-0.18	0.20	0.26^{**}	0.07	0.38
	(0.25)	(0.15)	(0.10)	(0.29)	(0.24)
in Low	-0.30	0.39^{***}	0.12	0.13	0.39^{**}
	(0.20)	(0.12)	(0.09)	(0.27)	(0.17)
in High	0.08	-0.23^{**}	0.03	0.19	-0.09
	(0.19)	(0.11)	(0.07)	(0.12)	(0.11)
[B] Employment-to-population ratio (in pp.)					
SDB Exposure	-0.01	0.02	0.06^{**}	-0.10^{**}	0.07^{**}
	(0.04)	(0.03)	(0.02)	(0.05)	(0.03)
in Agriculture	0.03	0.07	0.06	-0.12	0.26^{***}
	(0.06)	(0.06)	(0.05)	(0.08)	(0.06)
in Industry	-0.09	-0.01	0.02	-0.21^{***}	0.04
	(0.06)	(0.04)	(0.03)	(0.08)	(0.05)
in Service	-0.00	-0.00	0.16^{***}	-0.09	0.10
	(0.10)	(0.07)	(0.05)	(0.11)	(0.07)
in Low	-0.18^{**}	0.10^{*}	0.02	-0.09	0.15^{***}
	(0.07)	(0.05)	(0.04)	(0.08)	(0.05)
in High	0.07	-0.07	0.09^{***}	-0.09^{*}	-0.04
	(0.07)	(0.05)	(0.03)	(0.05)	(0.04)
[C] Average wage (in percent)					
SDB Exposure	-0.23^{*}	-0.23^{***}	0.07	0.12	0.14
	(0.14)	(0.08)	(0.11)	(0.12)	(0.10)
in Agriculture	-0.83^{***}	-0.28^{*}	0.14	-0.12	-0.48^{**}
	(0.27)	(0.16)	(0.19)	(0.31)	(0.20)
in Industry	0.30^{*}	-0.21^{**}	-0.00	0.04	0.04
	(0.16)	(0.08)	(0.17)	(0.17)	(0.11)
in Service	-0.20	-0.29	0.08	0.40	0.83^{***}
	(0.32)	(0.20)	(0.26)	(0.25)	(0.23)
in Low	0.08	-0.33^{**}	0.31^{*}	0.20	0.59^{***}
	(0.23)	(0.16)	(0.19)	(0.24)	(0.19)
in High	-0.24	0.20^{**}	-0.15	0.02	0.14
	(0.20)	(0.09)	(0.11)	(0.14)	(0.12)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on SDB exposure over the phases of the SDB's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the SDB's life cycle. SDB exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to SDB in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.10: Adjustments to robot exposure during robot investment cycles by cluster: OLS results

	OLS regression - Dep. var.: annualized change in the outcome variable			
	Industrial Robots			Robotics
	1995-2002	2002-2006	2006-2013	2013-2017
[A] Employment (in percent)				
ROB Exposure	0.23*	−0.53***	0.44***	0.09
	(0.12)	(0.09)	(0.09)	(0.08)
in Agriculture	0.27	−0.70***	0.65***	0.31*
	(0.27)	(0.22)	(0.24)	(0.16)
in Industry	0.29**	−0.33***	0.36***	0.01
	(0.12)	(0.10)	(0.10)	(0.09)
in Service	−0.08	−1.00***	0.48**	0.11
	(0.41)	(0.25)	(0.22)	(0.29)
in Low	0.34*	−0.39*	0.52***	−0.05
	(0.20)	(0.23)	(0.18)	(0.17)
in High	0.22	−0.65***	0.41***	0.01
	(0.15)	(0.10)	(0.09)	(0.08)
[B] Employment-to-population ratio (in pp.)				
ROB Exposure	0.21***	−0.14***	0.31***	−0.05**
	(0.04)	(0.03)	(0.04)	(0.03)
in Agriculture	0.24***	−0.17**	0.40***	−0.00
	(0.07)	(0.08)	(0.09)	(0.05)
in Industry	0.18***	−0.10***	0.26***	−0.07**
	(0.05)	(0.03)	(0.05)	(0.03)
in Service	0.27*	−0.31***	0.44***	−0.04
	(0.15)	(0.11)	(0.12)	(0.06)
in Low	0.27***	−0.16*	0.36***	−0.17***
	(0.06)	(0.08)	(0.08)	(0.04)
in High	0.16***	−0.16***	0.30***	−0.04
	(0.05)	(0.04)	(0.05)	(0.03)
[C] Average wage (in percent)				
ROB Exposure	−0.92***	−0.52***	0.04	0.43***
	(0.15)	(0.10)	(0.08)	(0.08)
in Agriculture	−1.58***	−0.65***	−0.16	0.30
	(0.35)	(0.20)	(0.26)	(0.19)
in Industry	−0.45***	−0.51***	0.11	0.44***
	(0.13)	(0.10)	(0.08)	(0.05)
in Service	−1.61***	−0.64	0.02	0.44
	(0.49)	(0.39)	(0.27)	(0.29)
in Low	−1.00***	−0.60**	−0.02	0.84***
	(0.24)	(0.28)	(0.17)	(0.14)
in High	−0.72***	−0.11	0.02	0.45***
	(0.17)	(0.11)	(0.08)	(0.07)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated OLS regressions of labor outcomes on robot exposure over the phases of the robot's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the robot's life cycle. Robot exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to robot in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.11: Adjustments to communication technology exposure during CT investment cycles by cluster: OLS results

	OLS regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2005	2005-2011	2011-2014	2014-2017
[A] Employment (in percent)					
CT Exposure	-0.34^{***}	-0.24^{***}	-0.06	-0.40^{***}	-0.02
	(0.10)	(0.09)	(0.07)	(0.10)	(0.08)
in Agriculture	-0.58^{***}	-0.04	0.08	-0.76^{***}	-0.17
	(0.21)	(0.27)	(0.24)	(0.20)	(0.17)
in Industry	-0.10	-0.11	0.10	-0.20^{*}	0.08
	(0.12)	(0.12)	(0.12)	(0.11)	(0.13)
in Service	-0.53^{**}	-0.35^{**}	-0.26^{*}	-0.45^{**}	-0.07
	(0.20)	(0.17)	(0.14)	(0.22)	(0.13)
in Low	-0.29^{*}	-0.36^{***}	-0.11	-1.01^{***}	0.62^{***}
	(0.16)	(0.11)	(0.09)	(0.23)	(0.20)
in High	-0.23^{*}	-0.22	0.08	-0.02	-0.25^{***}
	(0.13)	(0.17)	(0.16)	(0.09)	(0.08)
[B] Employment-to-population ratio (in pp.)					
CT Exposure	-0.07^{**}	-0.01	-0.00	-0.18^{***}	-0.03
	(0.03)	(0.03)	(0.04)	(0.03)	(0.03)
in Agriculture	-0.06	0.00	0.10	-0.24^{***}	-0.01
	(0.05)	(0.10)	(0.12)	(0.06)	(0.06)
in Industry	-0.02	0.01	0.12	-0.13^{***}	-0.00
	(0.05)	(0.04)	(0.08)	(0.04)	(0.05)
in Service	-0.17^{**}	-0.04	-0.08	-0.15^{**}	-0.04
	(0.08)	(0.08)	(0.10)	(0.06)	(0.04)
in Low	0.01	-0.02	-0.02	-0.34^{***}	0.24^{***}
	(0.05)	(0.04)	(0.06)	(0.06)	(0.06)
in High	-0.08^{*}	-0.06	0.07	-0.08^{***}	-0.09^{***}
	(0.05)	(0.08)	(0.09)	(0.03)	(0.03)
[C] Average wage (in percent)					
CT Exposure	0.28^{**}	0.95^{***}	-0.07	0.18	-0.13
	(0.11)	(0.11)	(0.07)	(0.12)	(0.08)
in Agriculture	0.32	1.10^{***}	-0.03	0.11	0.13
	(0.23)	(0.32)	(0.26)	(0.38)	(0.19)
in Industry	0.41^{***}	1.04^{***}	-0.19^{**}	0.04	-0.16
	(0.13)	(0.13)	(0.09)	(0.16)	(0.11)
in Service	0.33	0.51^{**}	-0.31	0.04	-0.29^{**}
	(0.24)	(0.25)	(0.21)	(0.21)	(0.14)
in Low	0.28	0.94^{***}	-0.08	0.07	-1.05^{***}
	(0.19)	(0.16)	(0.11)	(0.24)	(0.21)
in High	0.20	0.37^{**}	-0.25^{**}	-0.04	-0.03
	(0.14)	(0.15)	(0.12)	(0.17)	(0.09)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated OLS regressions of labor outcomes on CT exposure over the phases of the CT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the CT's life cycle. CT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to CT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.12: Adjustments to information technology exposure during IT investment cycles by cluster: OLS results

	OLS regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2004	2004-2008	2008-2014	2014-2017
[A] **Employment** (in percent)					
IT Exposure	0.22**	−0.46***	0.11	−0.19*	−0.09
	(0.11)	(0.10)	(0.07)	(0.10)	(0.09)
in Agriculture	0.28	−0.42*	0.39**	−0.05	−0.42**
	(0.29)	(0.24)	(0.19)	(0.25)	(0.18)
in Industry	0.18	−0.27**	0.17*	−0.27*	−0.05
	(0.12)	(0.13)	(0.10)	(0.14)	(0.11)
in Service	−0.05	−0.84***	−0.19*	−0.01	−0.08
	(0.24)	(0.24)	(0.11)	(0.14)	(0.20)
in Low	−0.20	−0.44*	−0.13	0.19	−0.88***
	(0.28)	(0.23)	(0.15)	(0.24)	(0.31)
in High	0.35***	−0.29***	0.28***	−0.38***	0.10
	(0.11)	(0.10)	(0.06)	(0.09)	(0.09)
[B] **Employment-to-population ratio** (in pp.)					
IT Exposure	0.11***	−0.17***	0.06***	−0.13***	−0.06**
	(0.04)	(0.04)	(0.02)	(0.03)	(0.03)
in Agriculture	0.02	−0.15	0.11	−0.13*	−0.23***
	(0.08)	(0.09)	(0.07)	(0.08)	(0.07)
in Industry	0.07	−0.11**	0.10***	−0.17***	−0.06
	(0.05)	(0.04)	(0.04)	(0.06)	(0.04)
in Service	0.11	−0.32**	−0.06	−0.06	−0.04
	(0.09)	(0.12)	(0.04)	(0.05)	(0.06)
in Low	0.00	−0.01	0.03	−0.04	−0.62***
	(0.09)	(0.10)	(0.05)	(0.07)	(0.09)
in High	0.14***	−0.17***	0.09***	−0.15***	0.02
	(0.04)	(0.05)	(0.02)	(0.04)	(0.03)
[C] **Average wage** (in percent)					
IT Exposure	−0.01	−0.04	0.10	0.11	−0.11
	(0.12)	(0.13)	(0.10)	(0.09)	(0.10)
in Agriculture	−0.17	0.08	0.22	0.27	0.18
	(0.32)	(0.36)	(0.21)	(0.29)	(0.21)
in Industry	0.38***	−0.22	0.16	−0.07	−0.11
	(0.14)	(0.14)	(0.16)	(0.12)	(0.10)
in Service	−0.17	0.09	0.06	0.20	−0.20
	(0.28)	(0.31)	(0.23)	(0.12)	(0.21)
in Low	0.23	−0.29	−0.08	0.40*	0.17
	(0.32)	(0.36)	(0.22)	(0.22)	(0.32)
in High	0.06	0.05	0.10	0.10	−0.09
	(0.12)	(0.08)	(0.08)	(0.10)	(0.10)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated OLS regressions of labor outcomes on IT exposure over the phases of the IT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the IT's life cycle. IT exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to IT in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.13: Adjustments to software and database exposure during SDB investment cycles by cluster: OLS results

	OLS regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2000	2000-2005	2005-2008	2008-2014	2014-2017
[A] Employment (in percent)					
SDB Exposure	-0.02	0.13^{*}	0.12^{**}	-0.03	0.22^{**}
	(0.12)	(0.07)	(0.06)	(0.12)	(0.09)
in Agriculture	0.36	0.08	0.14	-0.32	0.72^{***}
	(0.25)	(0.16)	(0.15)	(0.30)	(0.19)
in Industry	-0.24^{*}	0.11	0.01	-0.18	0.03
	(0.15)	(0.10)	(0.07)	(0.21)	(0.12)
in Service	-0.22	0.04	0.23^{**}	-0.14	0.37
	(0.24)	(0.16)	(0.09)	(0.20)	(0.23)
in Low	-0.37	0.41^{***}	0.12	-0.13	0.41^{**}
	(0.23)	(0.11)	(0.09)	(0.24)	(0.17)
in High	0.17	-0.20^{*}	0.07	0.16	-0.14
	(0.17)	(0.11)	(0.07)	(0.11)	(0.10)
[B] Employment-to-population ratio (in pp.)					
SDB Exposure	0.02	0.01	0.07^{***}	-0.06	0.07^{**}
	(0.04)	(0.03)	(0.02)	(0.04)	(0.03)
in Agriculture	0.04	0.05	0.07	-0.11	0.27^{***}
	(0.07)	(0.06)	(0.06)	(0.09)	(0.07)
in Industry	-0.06	0.01	0.01	-0.10	0.04
	(0.06)	(0.04)	(0.03)	(0.09)	(0.05)
in Service	0.03	-0.06	0.16^{***}	-0.08	0.10
	(0.10)	(0.07)	(0.05)	(0.07)	(0.07)
in Low	-0.18^{**}	0.07	0.03	-0.08	0.16^{***}
	(0.08)	(0.05)	(0.04)	(0.07)	(0.05)
in High	0.09	-0.06	0.11^{***}	-0.05	-0.04
	(0.06)	(0.05)	(0.03)	(0.05)	(0.04)
[C] Average wage (in percent)					
SDB Exposure	-0.31^{**}	-0.27^{***}	0.06	0.15	0.10
	(0.14)	(0.09)	(0.11)	(0.11)	(0.10)
in Agriculture	-0.90^{***}	-0.42^{**}	0.07	-0.03	-0.51^{**}
	(0.29)	(0.19)	(0.21)	(0.35)	(0.21)
in Industry	0.19	-0.24^{**}	0.02	0.32^{*}	0.07
	(0.16)	(0.10)	(0.17)	(0.18)	(0.11)
in Service	-0.25	-0.21	0.06	0.06	0.59^{**}
	(0.30)	(0.22)	(0.24)	(0.18)	(0.24)
in Low	0.03	-0.43^{***}	0.26	0.48^{**}	0.50^{***}
	(0.26)	(0.16)	(0.19)	(0.23)	(0.18)
in High	-0.23	0.17^{*}	-0.17	-0.07	0.14
	(0.18)	(0.10)	(0.11)	(0.12)	(0.12)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated OLS regressions of labor outcomes on SDB exposure over the phases of the SDB's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the SDB's life cycle. SDB exposure is calculated using the shift-share method and subsequently standardized at the phase level. Therefore, the coefficient can be interpreted as a 1-STD change in exposure to SDB in each phase. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.14: Adjustments to robot exposure during robot investment cycles by cluster: results without standardisation

	IV regression - Dep. var.: annualized change in the outcome variable			
	Industrial Robots			Robotics
	1995-2002	2002-2006	2006-2013	2013-2017
[A] **Employment** (in percent)				
ROB Exposure	1.43	-6.82^{***}	8.36^{***}	0.89
	(1.40)	(1.09)	(1.33)	(0.77)
in Agriculture	0.71	-6.83^{***}	11.01^{***}	2.09^{*}
	(2.69)	(2.41)	(2.81)	(1.20)
in Industry	2.98^{**}	-5.47^{***}	8.11^{***}	-0.25
	(1.47)	(1.32)	(1.97)	(0.95)
in Service	-0.83	-8.58^{***}	5.57^{**}	1.29
	(3.71)	(2.49)	(2.73)	(2.28)
in Low	2.69	-6.60^{**}	7.84^{***}	-1.10
	(2.19)	(2.64)	(2.57)	(1.49)
in High	1.72	-8.77^{***}	8.26^{***}	0.68
	(1.87)	(1.21)	(1.41)	(0.83)
[B] **Employment-to-population ratio** (in pp.)				
ROB Exposure	2.06^{***}	-1.73^{***}	5.40^{***}	-0.47^{*}
	(0.46)	(0.39)	(0.60)	(0.24)
in Agriculture	1.95^{***}	-1.35	5.69^{***}	-0.08
	(0.66)	(0.87)	(1.09)	(0.38)
in Industry	2.07^{***}	-1.60^{***}	5.66^{***}	-0.95^{**}
	(0.58)	(0.39)	(1.01)	(0.38)
in Service	2.29	-2.44^{**}	5.05^{***}	-0.09
	(1.44)	(1.07)	(1.48)	(0.50)
in Low	2.83^{***}	-2.16^{**}	5.43^{***}	-1.64^{***}
	(0.66)	(1.01)	(1.16)	(0.37)
in High	1.71^{**}	-2.13^{***}	5.36^{***}	-0.35
	(0.67)	(0.50)	(0.71)	(0.28)
[C] **Average wage** (in percent)				
ROB Exposure	-10.81^{***}	-6.62^{***}	0.78	3.91^{***}
	(1.65)	(1.25)	(1.35)	(0.74)
in Agriculture	-14.60^{***}	-7.14^{***}	-3.19	2.44^{*}
	(3.34)	(2.10)	(3.33)	(1.44)
in Industry	-5.71^{***}	-7.74^{***}	2.43	4.56^{***}
	(1.74)	(1.39)	(1.61)	(0.57)
in Service	-16.68^{***}	-7.34^{*}	0.47	3.93^{*}
	(4.41)	(3.72)	(3.31)	(2.09)
in Low	-12.22^{***}	-7.89^{**}	0.08	6.50^{***}
	(2.55)	(3.34)	(2.61)	(1.30)
in High	-8.85^{***}	-1.02	1.06	4.59^{***}
	(2.13)	(1.32)	(1.44)	(0.74)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on robot exposure over the phases of the robot's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the robot's life cycle. Robot exposure is calculated using the shift-share method. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.15: Adjustments to communication technology exposure during CT investment cycles by cluster: results without standardisation

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2005	2005-2011	2011-2014	2014-2017
[A] Employment (in percent)					
CT Exposure	-6.60^{***}	-6.45^{**}	-2.59	-6.23^{***}	-0.04
	(2.07)	(2.67)	(2.26)	(1.64)	(1.55)
in Agriculture	-10.89^{***}	1.56	-0.71	-10.82^{***}	-0.84
	(3.86)	(6.42)	(6.15)	(2.80)	(2.44)
in Industry	-1.31	-3.62	2.65	-2.82	2.38
	(2.33)	(3.67)	(4.58)	(1.84)	(2.32)
in Service	-11.75^{**}	-9.59^{*}	-5.81^{*}	-5.75	-1.21
	(4.49)	(5.44)	(3.38)	(3.61)	(3.47)
in Low	-5.50^{*}	-11.66^{***}	-4.11	-15.97^{***}	13.20^{***}
	(3.20)	(3.47)	(3.01)	(3.69)	(3.63)
in High	-5.21^{*}	0.18	-2.77	0.09	-5.34^{***}
	(2.77)	(4.72)	(4.57)	(1.38)	(1.81)
[B] Employment-to-population ratio (in pp.)					
CT Exposure	-1.15	-0.14	-0.33	-2.69^{***}	-0.49
	(0.72)	(1.07)	(1.29)	(0.48)	(0.55)
in Agriculture	-1.18	1.17	1.29	-3.23^{***}	0.36
	(1.01)	(2.53)	(2.95)	(0.87)	(0.85)
in Industry	-0.44	-0.15	3.90	-1.70^{***}	0.36
	(0.94)	(1.25)	(2.86)	(0.64)	(0.91)
in Service	-3.05	-0.00	-0.93	-2.79^{***}	-1.15
	(1.83)	(2.61)	(2.33)	(1.00)	(0.98)
in Low	0.48	-1.15	-0.93	-5.22^{***}	4.73^{***}
	(1.02)	(1.38)	(1.84)	(1.04)	(1.10)
in High	-1.50	1.48	-1.05	-1.10^{**}	-2.07^{***}
	(1.05)	(2.17)	(2.40)	(0.48)	(0.66)
[C] Average wage (in percent)					
CT Exposure	4.84^{**}	29.14^{***}	-2.20	1.73	-1.35
	(2.27)	(3.17)	(2.32)	(1.99)	(1.69)
in Agriculture	6.33	26.75^{***}	4.40	-0.02	1.79
	(4.18)	(7.15)	(6.24)	(5.33)	(2.69)
in Industry	6.53^{**}	35.43^{***}	-7.95^{**}	1.67	-1.65
	(2.69)	(3.85)	(3.22)	(2.61)	(2.05)
in Service	4.91	12.93^{*}	-7.98	-0.50	-9.08^{**}
	(5.27)	(7.62)	(5.21)	(3.35)	(3.38)
in Low	4.17	31.98^{***}	-3.08	2.79	-17.71^{***}
	(3.52)	(4.98)	(3.55)	(3.60)	(3.97)
in High	3.87	6.87	-2.19	-2.16	1.24
	(2.89)	(4.14)	(3.40)	(2.68)	(2.02)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on CT exposure over the phases of the CT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the CT's life cycle. CT exposure is calculated using the shift-share method. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.16: Adjustments to information technology exposure during IT investment cycles by cluster: results without standardisation

	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2001	2001-2004	2004-2008	2008-2014	2014-2017
[A] Employment (in percent)					
IT Exposure	3.29	-15.73^{***}	2.20	-4.89^{**}	-2.46^{*}
	(3.17)	(3.72)	(1.38)	(2.10)	(1.44)
in Agriculture	6.29	-11.23	5.51^{*}	-1.70	-6.31^{**}
	(7.15)	(8.72)	(3.13)	(3.77)	(2.69)
in Industry	4.42	-11.41^{**}	3.07^{*}	-4.27	-1.82
	(3.21)	(4.45)	(1.77)	(2.56)	(1.76)
in Service	-5.48	-28.23^{***}	-5.53^{**}	-2.56	-1.90
	(7.28)	(8.78)	(2.56)	(4.01)	(3.78)
in Low	-10.18	-17.51^{**}	-2.23	1.83	-15.18^{***}
	(6.84)	(7.69)	(2.55)	(5.36)	(4.76)
in High	8.83^{**}	-9.62^{**}	6.03^{***}	-9.36^{***}	0.74
	(3.41)	(3.72)	(1.38)	(1.69)	(1.41)
[B] Employment-to-population ratio (in pp.)					
IT Exposure	2.11^{*}	-5.04^{***}	1.46^{***}	-2.74^{***}	-1.32^{**}
	(1.10)	(1.60)	(0.49)	(0.71)	(0.51)
in Agriculture	0.19	-3.15	1.43	-2.09^{*}	-3.45^{***}
	(1.88)	(3.37)	(1.12)	(1.14)	(0.94)
in Industry	1.69	-4.81^{***}	1.95^{***}	-2.60^{**}	-1.19^{*}
	(1.30)	(1.59)	(0.67)	(1.04)	(0.69)
in Service	1.26	-9.82^{**}	-1.09	-2.02	-0.81
	(2.97)	(4.50)	(1.04)	(1.50)	(1.07)
in Low	-0.74	-0.77	0.99	0.36	-9.48^{***}
	(2.19)	(3.25)	(0.92)	(1.71)	(1.44)
in High	3.12^{**}	-4.67^{**}	1.84^{***}	-3.52^{***}	0.03
	(1.29)	(1.77)	(0.57)	(0.72)	(0.51)
[C] Average wage (in percent)					
IT Exposure	1.00	-0.23	1.92	2.35	-1.95
	(3.47)	(4.67)	(1.96)	(1.90)	(1.57)
in Agriculture	-1.37	8.05	4.24	3.20	2.71
	(7.75)	(12.17)	(3.46)	(4.52)	(2.96)
in Industry	9.43^{**}	-7.09	3.29	0.47	-1.21
	(3.70)	(5.11)	(2.90)	(2.30)	(1.56)
in Service	-4.41	-2.97	-1.21	3.08	-6.02
	(8.55)	(11.09)	(5.33)	(3.53)	(3.68)
in Low	7.85	6.17	-1.54	12.25^{**}	-0.35
	(7.53)	(11.70)	(3.78)	(4.88)	(5.21)
in High	2.18	0.81	3.35^{*}	0.55	-1.45
	(3.56)	(2.86)	(1.84)	(1.98)	(1.58)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on IT exposure over the phases of the IT's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the IT's life cycle. IT exposure is calculated using the shift-share method. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

Table C.17: Adjustments to software and database exposure during SDB investment cycles by cluster: results without standardisation

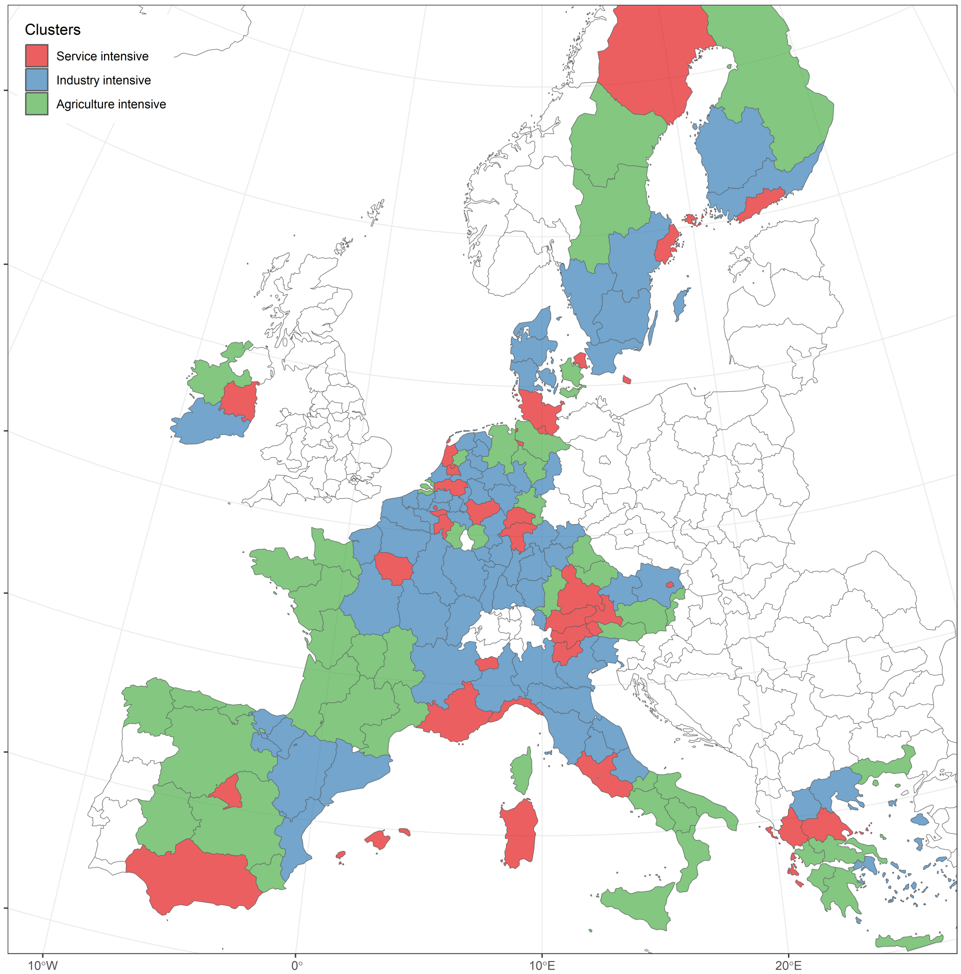
	IV regression - Dep. var.: annualized change in the outcome variable				
	Web 1.0		GUI - CC		Big Data - AI
	1995-2000	2000-2005	2005-2008	2008-2014	2014-2017
[A] Employment (in percent)					
SDB Exposure	-0.99	1.58	0.63^{*}	0.16	1.80^{**}
	(1.36)	(0.98)	(0.38)	(1.60)	(0.70)
in Agriculture	3.26	1.11	0.80	-1.95	4.88^{***}
	(2.61)	(2.04)	(0.93)	(3.04)	(1.29)
in Industry	-3.37^{**}	0.56	0.12	-4.24^{*}	0.35
	(1.62)	(1.38)	(0.45)	(2.25)	(0.93)
in Service	-2.06	2.60	1.71^{**}	0.81	2.75
	(2.76)	(2.01)	(0.64)	(3.40)	(1.76)
in Low	-3.37	5.23^{***}	0.77	1.50	2.86^{**}
	(2.28)	(1.60)	(0.58)	(3.12)	(1.25)
in High	0.92	-3.01^{**}	0.22	2.19	-0.66
	(2.13)	(1.51)	(0.49)	(1.38)	(0.78)
[B] Employment-to-population ratio (in pp.)					
SDB Exposure	-0.15	0.27	0.38^{**}	-1.15^{**}	0.54^{**}
	(0.49)	(0.39)	(0.17)	(0.54)	(0.25)
in Agriculture	0.29	0.90	0.38	-1.40	1.86^{***}
	(0.70)	(0.80)	(0.34)	(0.92)	(0.45)
in Industry	-0.96	-0.12	0.12	-2.44^{***}	0.29
	(0.65)	(0.47)	(0.23)	(0.91)	(0.37)
in Service	-0.01	-0.03	1.05^{***}	-1.11	0.74
	(1.14)	(0.97)	(0.34)	(1.27)	(0.50)
in Low	-1.98^{**}	1.32^{*}	0.14	-1.02	1.09^{***}
	(0.76)	(0.67)	(0.27)	(0.99)	(0.38)
in High	0.76	-0.86	0.60^{***}	-1.09^{*}	-0.26
	(0.81)	(0.65)	(0.21)	(0.59)	(0.28)
[C] Average wage (in percent)					
SDB Exposure	-2.56^{*}	-3.06^{***}	0.46	1.41	0.98
	(1.54)	(1.07)	(0.73)	(1.44)	(0.76)
in Agriculture	-9.26^{***}	-3.76^{*}	0.93	-1.47	-3.51^{**}
	(3.00)	(2.18)	(1.26)	(3.64)	(1.42)
in Industry	3.39^{*}	-2.76^{**}	-0.03	0.47	0.32
	(1.78)	(1.11)	(1.12)	(2.02)	(0.82)
in Service	-2.26	-3.90	0.51	4.73	6.05^{***}
	(3.62)	(2.70)	(1.70)	(2.99)	(1.71)
in Low	0.86	-4.40^{**}	2.05^{*}	2.33	4.27^{***}
	(2.55)	(2.08)	(1.23)	(2.84)	(1.36)
in High	-2.72	2.64^{**}	-1.03	0.22	1.02
	(2.23)	(1.23)	(0.72)	(1.62)	(0.87)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on SDB exposure over the phases of the SDB's life cycle in the different types of regions. The dependent variables represent the annual change in regional employment (in log-difference), employment-to-population ratio, and average wage (in log-difference) during the phases of the SDB's life cycle. SDB exposure is calculated using the shift-share. Control variables include changes in trade exposure, final demand (both measured using shift-share), and exposure to other technologies. We cluster regions using a k-means algorithm using the share of employment in Agriculture, Industry, and Services in each region in 1980. To distinguish productivity, we classify regions as high (low) productive if their productivity level in 1980 is above (below) the median.

D Additional Figures

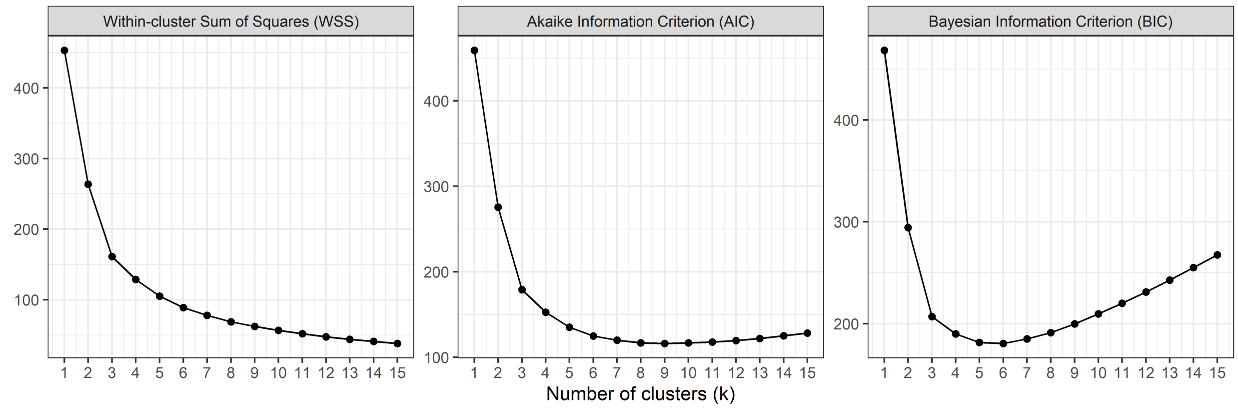
Figure D.1 shows the geographical distribution of regions according to our clustering strategy.

Figure D.1: Clusters of regions according to productive specialization



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

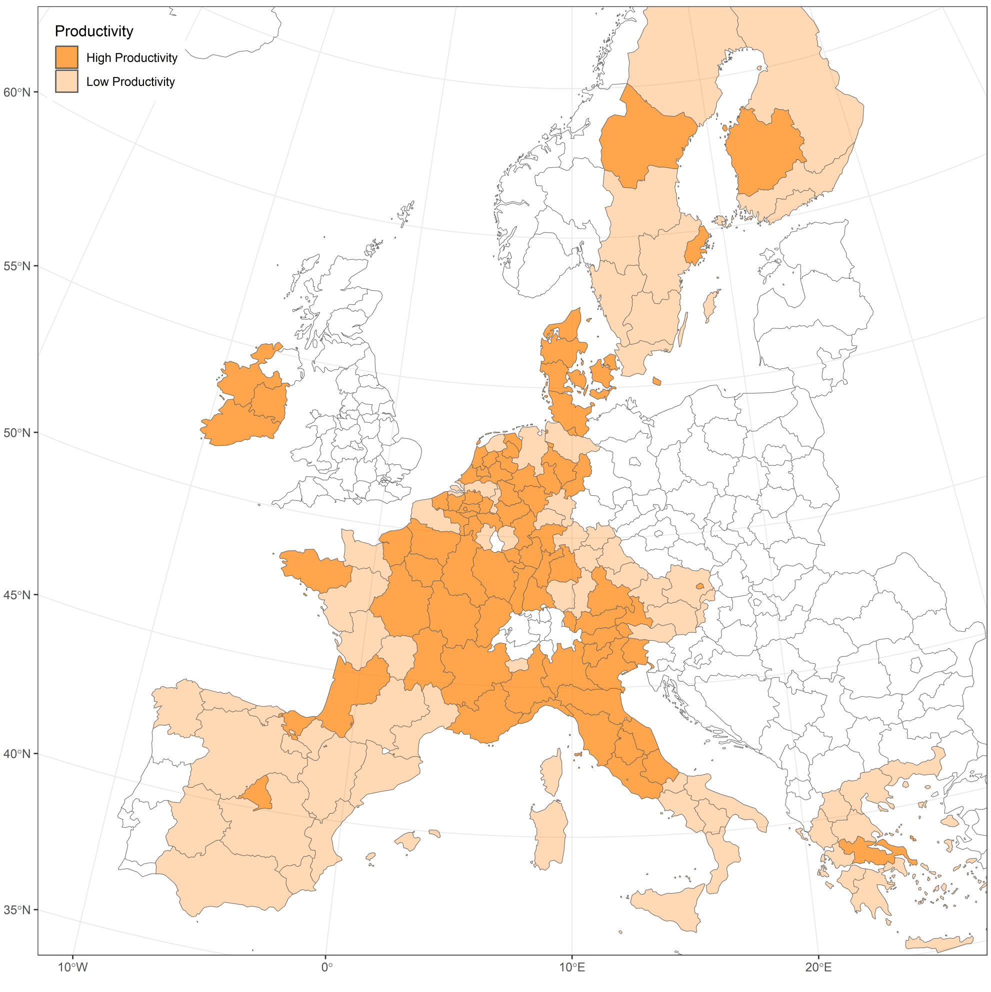
Figure D.2: Measures of goodness-of-fit



Notes: This figure presents the goodness-of-fit for a great number of clusters going from 1 to 15. We use three indicators to assess the goodness-of-fit: the Within-cluster Sum of Squares (WSS), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

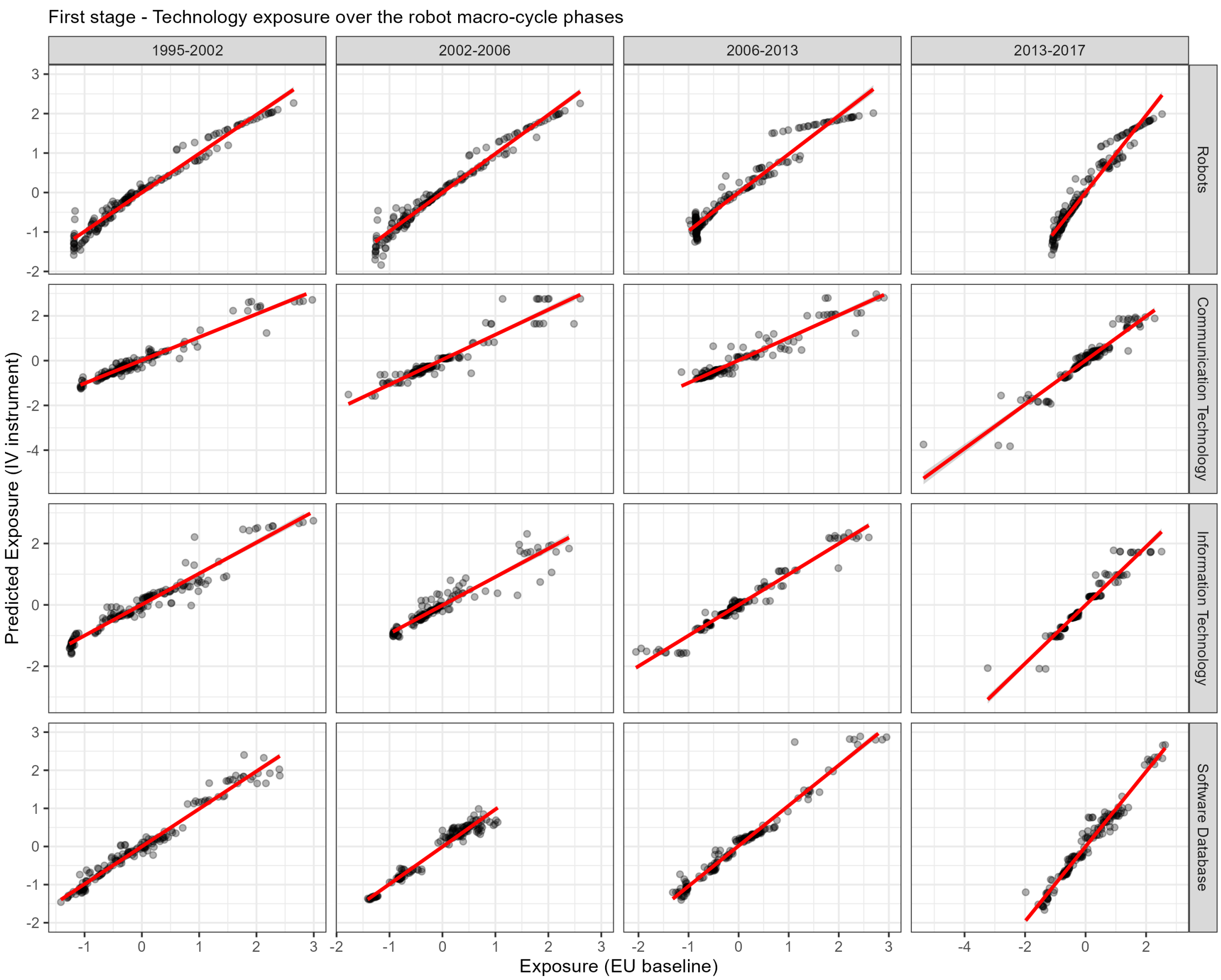
Figure D.3 shows the geographical distribution of regions according to their labor productivity level in 1980. Regions are categorized as 'High (Low)-productivity' if their productivity is above (below) the median of the entire sample of regions.

Figure D.3: Clusters of regions according to their labor productivity level



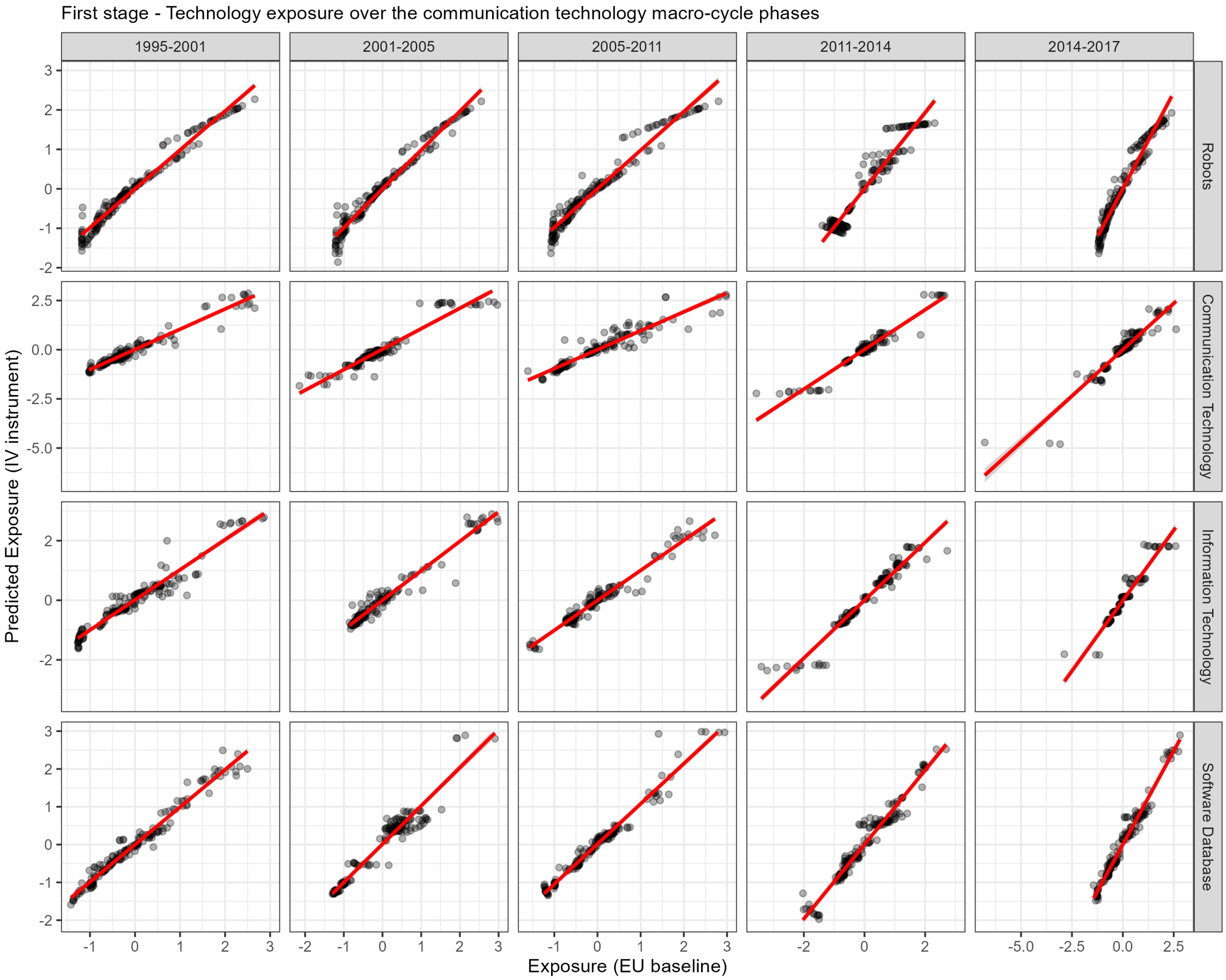
Notes: This figure presents the divide of regions according to their productivity level in 1980. We compute the clusters by using a K-means algorithm. The variables employed for the clustering are the shares of employment in agriculture, industry, and services in 1980. We standardize the variables at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

Figure D.4: Technology exposure during robot investment cycles (First stage)



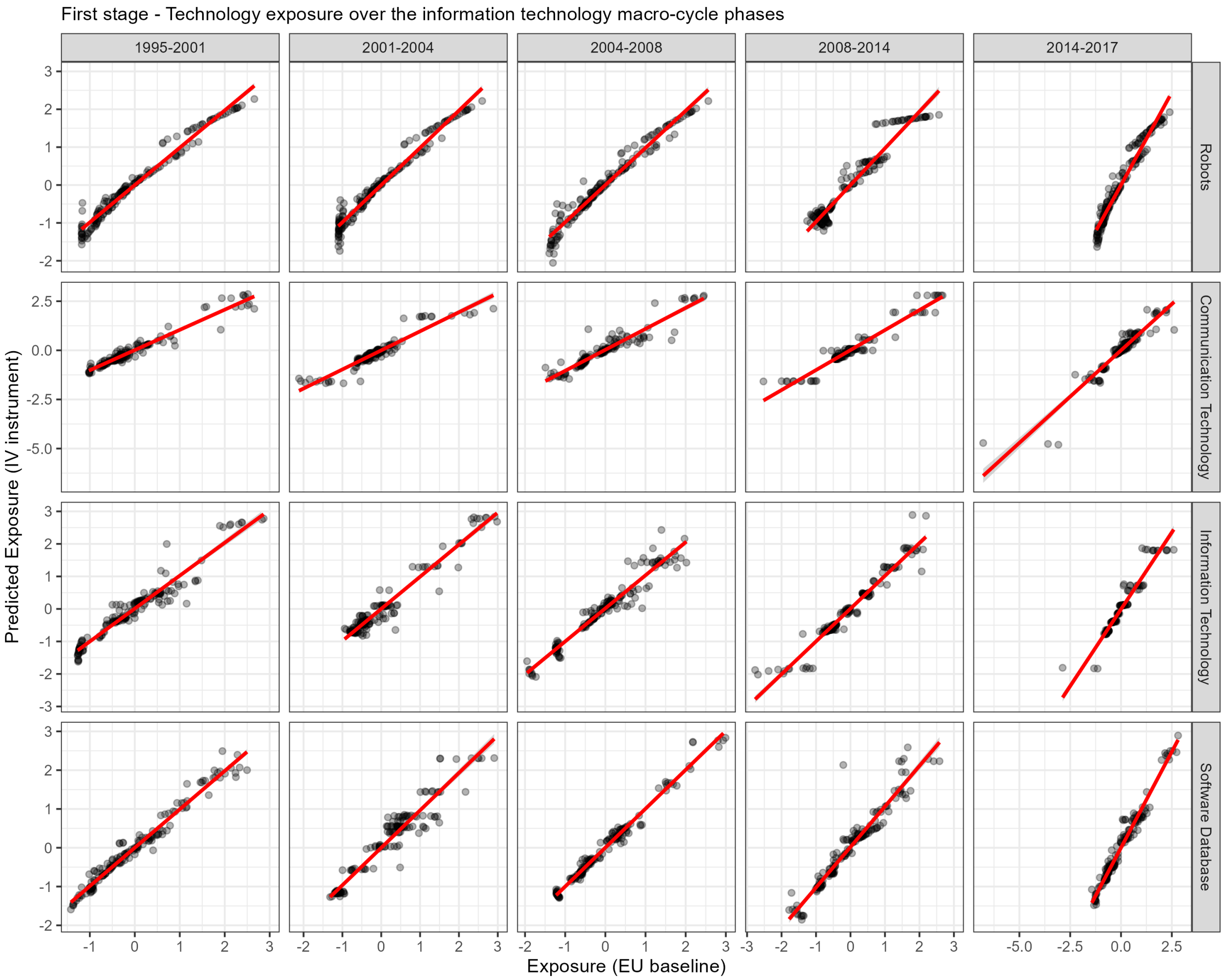
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by robot investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed effects. Both exposures are computed with a shift-share using the employment sectoral shares from European regions in 1980.

Figure D.5: Technology exposure during communication technology investment cycles (First stage)



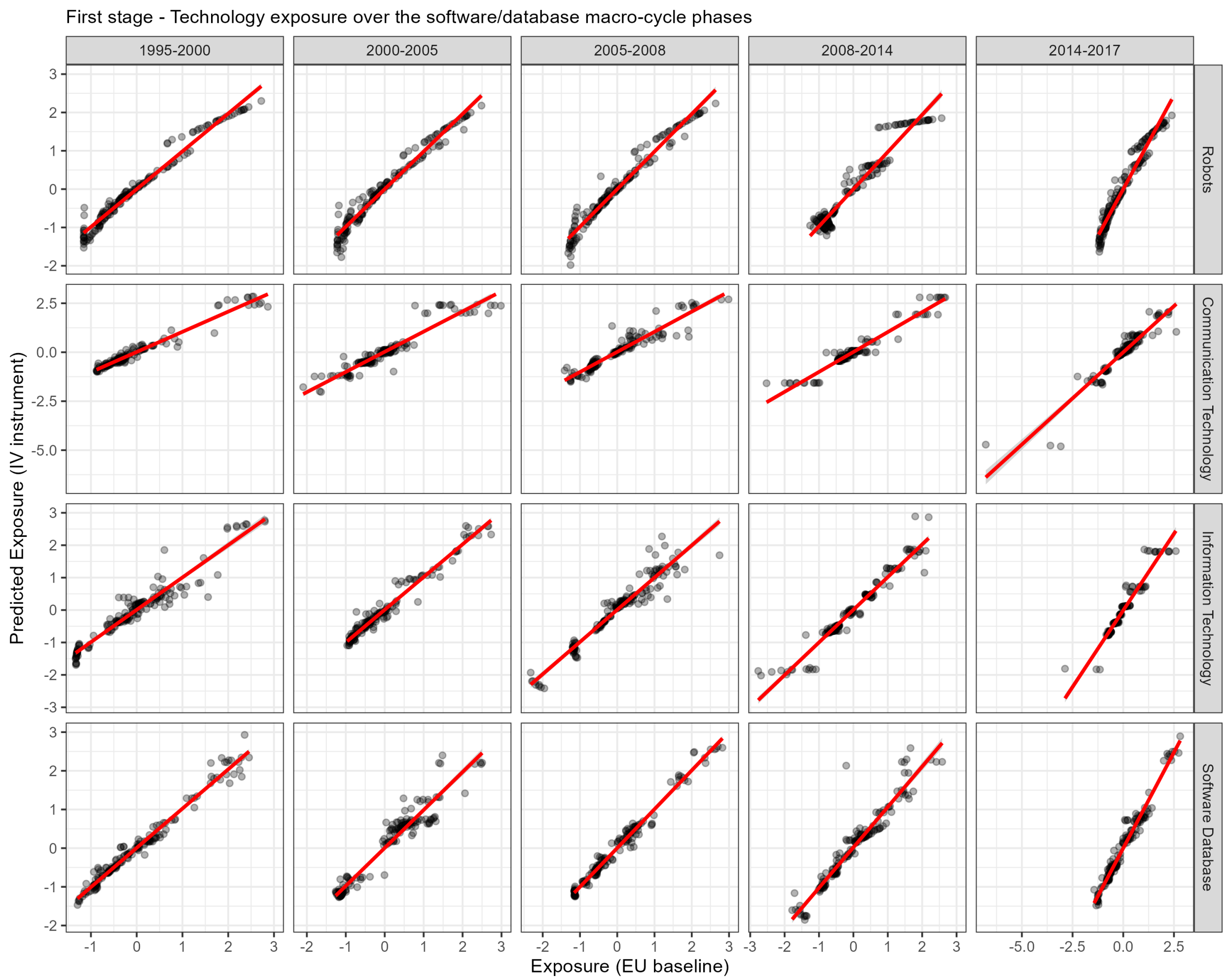
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by CT investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed effects. Both exposures are computed with a shift-share using the employment sectoral shares from European regions in 1980.

Figure D.6: Technology exposure during information technology investment cycles (First stage)



Notes: This figure presents the first-stage regressions for the technology exposure in European regions by IT investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed effects. Both exposures are computed with a shift-share using the employment sectoral shares from European regions in 1980.

Figure D.7: Technology exposure during software database investment cycles (First stage)



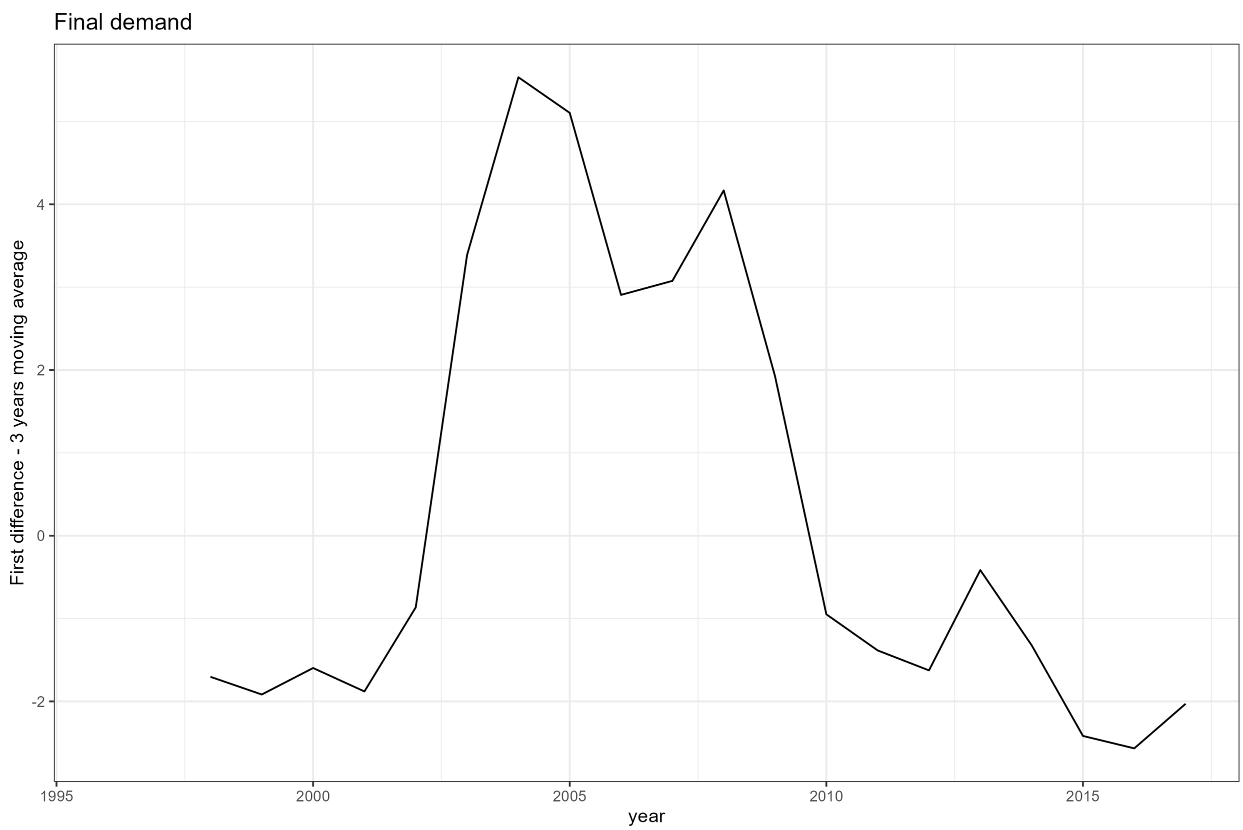
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by SDB investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed effects. Both exposures are computed with a shift-share using the employment sectoral shares from European regions in 1980.

D.1 Technology stock

Figure D.8 shows the evolution of the first difference in the real consumption per 1000 worker at the EU level (aggregated for the 12 European countries in the sample). The series has been smoothed by taking the 3-year moving average.

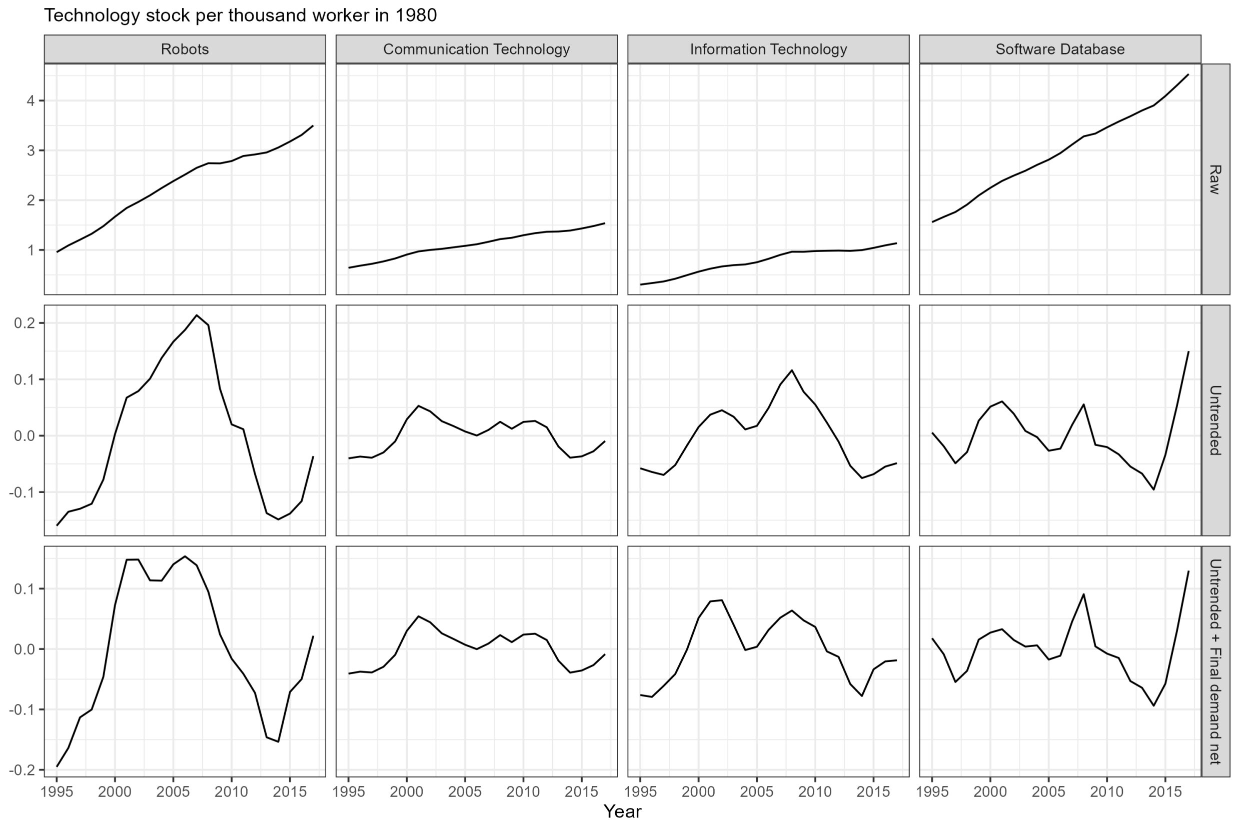
Figure D.9 presents the technology stocks (per thousand workers in 1980) from 1995 to 2017, expressed as an index, for robots, communication technology, information technology, and software and databases. The first row of panels displays the raw time series, which is increasing for all technologies. 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.8: Evolution of final demand. First difference (3-year moving average)



Notes: Figure D.8 shows the evolution of the difference in real consumption per 1000 workers at the European level (this is, aggregated for the 12 European countries in the sample). The series has been smoothed by taking the 3-year moving average. The data on consumption correspond to the final consumption expenditure of households from the OCED 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).

Figure D.9: Technology stocks per thousand workers in 1980



Notes: Figure D.9 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).

E Technological Cycles: Summarizing Major Developments

E.1 Cycle 1.: Web 1.0 (1990–)

Table E.1 outlines the major technological developments in the early 1900s, which were diffused during the first cycle.

Table E.1: Technologies that characterized cycle 1. 1990-2004–

Computational power	1993: Intel Pentium microprocessor (Intel)
	1980s Personal computers
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)

Advancements in mainframes and microcomputers began in the 1960s and 1970s. However, it was only with the reduction in the price and size of microprocessors that personal computers became available for use in administrative tasks and smaller firms (Malerba et al. 1999, Freeman and Louçã 2001).[28] Concurrently, the development of newer and more user-friendly operating systems such as Windows 3.0 in 1990, the open-source operating system Linux in 1991, and Windows 1995 further facilitated widespread adoption.

In contrast to previous decades when the Internet was confined to researchers and engineers, the number of Internet hosts experienced a significant increase in the late 1990s (Mowery and Simcoe 2002). This surge was facilitated by firms adopting computer hardware (as mentioned above), development of the HTTP protocol and the HTML language, and the introduction of 'browsers' or platforms designed for reading HTML documents (Mowery and Simcoe 2002). HTML and HTTP which were introduced in the 1990s, enabled the inclusion of multimedia content in web pages and the possibility of cross-referencing sources, allowing quick access to a vast number of multimedia pages. This gave rise to the WWW in 1991, marking one of the critical developments of this first cycle. The MOSAIC and Netscape browsers were introduced in 1993 and 1995 respectively, and simplified and standardized the visualization of documents online.

By 2002, over 50% of firms with 10 or more employees were utilizing the Internet (Pilat 2005).[29] The dramatic diffusion of the Internet changed retail dynamics and gave rise to online commerce (Mowery and Simcoe 2002). Major online retail companies such as Amazon.com and eBay, started operating in 1995. By 2001, a significant percentage of companies in Europe were utilizing the Internet for sales or purchases (Mowery and Simcoe 2002).

The adoption of ICT triggered significant changes to firms' organizational structures and affected business organization, communication with customers and suppliers, and work practices. ICT replaced various activities and particularly those more easily codified and programmed, and created new tasks. Qualitative firm level research provides evidence of these changes. Autor et al. (2002) offer an interesting case study of adoption of check imaging and optical character recognition of OCR software by a U.S. bank. On the one hand, the technology facilitated automated check reading and made electronic checks available for all workers. This led to the reorganization of certain activities and resulted in more specialized employment. Specifically, before the introduction of digitalization, in 1994 an activity such as check exception examination involved around 650 clerks. Since there was a requirement for a physical check, one worker oversaw the entire process per check. After

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

[29] The percentage varies by country, with Japan and the Scandinavian countries leading adoption, with almost all firms using the Internet.

adoption of OCR software checks were accessible electronically and could be accessed by multiple workers simultaneously which resulted in a break down into more specialized tasks related to processing overdrafts, implementing stop payment orders, and verifying signatures (Autor et al. 2002).

E.2 Cycle 2.: Graphical User Interface and Cloud Computing (2004–)

Table E.2 summarizes the major technological developments in the Graphical User Interface and Cloud Computing cycle.

Table E.2: Technologies that characterized cycle 2. 2004–

Communication Software	Web 2.0	2004 Flickr developed it's own API 2006 Facebook and Twitter introduced their own API 2014 Apache Flink is introduced in Apache 2008 AppStore 2012 Google Play
Hardware	Cloud Computing	2006 Elastic Compute Cloud Commercial Services (EC2), GoogleDocs 2010 Microsoft and other companies provide private CC services

Notes: Own elaboration based on Lane (2019)

Gradually, developments in the internet led to a newer phase known as 'Web 2.0.' There is no precise definition of Web 2.0, rather it is described in terms of the dimensions it encompasses. These dimensions include technological aspects such as AJAX, RIA, and XML/DHTML, principles such as participation, collective intelligence, and a rich user experience, and applications and tools such as Wikipedia, Flickr, and Mashups (Kim et al. 2009). This phase is distinguished by perception of the Internet as a collaborative platform where users can contribute actively to the development and improvement of applications. During this period, social media platforms developed their own APIs to become the primary channels connecting individuals (Lane 2019). This facilitated the creation of new applications and services which were integrated seamlessly with social media platforms.[30]

Another notable feature of this phase is the increasing data intensity of applications, where improvement of these applications is also related to the number of users (O'Reilly 2007). Companies are building on the huge amounts of data flowing through social media platforms which are allowing them to tailor their advertising based on consumer preferences. Data analytics has shifted from reliance on structured data to reliance on unstructured data based on natural processing methods (Lee 2017). Cloud computing became more widespread in the 2000s and in 2006, Amazon introduced its Elastic Compute Cloud or EC2 commercial service for businesses. The less popular private clouds were available in 2008 and in

[30]In 2007, Apple initiated the 'App Revolution' by launching its software development kit for third parties. Developers were able to create apps accessible using an on any iPhone. The Apple App Store was launched in 2008 and was followed in 2012 by the introduction of Google Play (Crook 2018).

2010, Microsoft and other companies launched their own 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 although to varying intensity across countries.[31]

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 these services enabled the growth of start-ups and small and medium sized firms (Bloom and Pierri 2018, DeStefano et al. 2023). This outcome appears to be driven by the lower costs of cloud services compared to the high fixed costs of investments in ICT which represent a substantial entry barrier for new firms (Etro 2009). The creation of more smaller firms has consequences for employment. Since small and medium sized firms tend to be associated with high employment growth, their emergence enabled by cloud computing services is having positive effects on employment (Etro 2009, Bloom and Pierri 2018).

E.3 Cycle 3.: Big Data & Artificial Intelligence (2013–)

Table E.3 presents the major advances in the ongoing Big Data & Artificial Intelligence cycle.

Table E.3: Technologies that characterized cycle 3. 2013–

Communication Hardware	Internet of Things	2013 IoT becomes more widespread due to hardware platforms 2016 IoT products widely available in the market
Software	Big Data & Data analytics	2013 Hadoop 2.0, Apache spark, Apache Storm, Apache Samza are introduced 2014 Apache Flink is introduced in Apache 2015 Apache Apex Is introduced in Apache 2016 Zettabyte era begins
Software	Artificial intelligence (ML & DL algorithms)	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); Cao et al. (2018)

The spread of the IoT as a set of technologies enabling physical objects equipped with sensors to communicate and share data with computing systems through wired or wireless networks, without the need for human mediation is changing the way data is collected, shared, and transferred between objects (Lee 2017).[32] The IoT in conjunction with social media websites is becoming another significant source of data generation, including images, videos, and audio (Lee 2017). The technology is pervasive in a range of sectors including

[31] Over 60% of enterprises in Sweden, Finland, the Netherlands and Denmark use cloud computing. For detailed figures see EUROSTAT website.

[32] Objects are connected to the Internet and to each other through technologies such as Wireless Sensor Networks (WSN), Radio-frequency identification (RFID), Bluetooth, Near-field communication (NFC), Long Term Evolution (LTE), among others. This connectivity allows data to be collected, shared, and transferred between objects (Khanna and Kaur 2020).

aerospace and defense, agroindustry and precision agriculture, automotives, pharmaceuticals, consumer goods, chemicals, and ICT (Andreoni et al. 2021).[33]

Based on the widespread internet penetration in the previous period, big data and data analytics have experienced a significant surge. For instance, Gupta and Rani (2019) demonstrates that research publications associated with big data in 2017 had increased by 126 fold compared to 2011. This coincided with the creation of several big data processing platforms which became widely available in 2013 through incorporation into Apache Gupta and Rani 2019.[34] According to Gupta and Rani (2019), Apache Spark is one of the most popular systems for large-scale data processing and outperforms Hadoop (another Apache system) by working faster and utilizing in-memory processing rather than a file system (IBMCloud-Education 2021). Other platforms capable of real-time analytics and processing released in this period include Apache Storm and Apache Samza which are used to cybersecurity and threat detection, and performance monitoring, among other applications (Gupta and Rani 2019).[35] Overall, the compound annual growth of social media analytics is projected to be 27.6% between 2015 and 2020 (Lee 2017).

AI is attracting increased attention. AI is generally understood as a subset of computer science designed to train machines to perform cognitive activities associated to 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, both of which rely on the development of neural network techniques.

The ability of AI to perform various functions is leading to its application in several industries (Cockburn et al. 2018) to perform activities 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 the fact that while computerization allowed the codification of preexisting knowledge, primarily related to repetitive activities, machine learning empowers the machine to learn from examples to achieve a specific output (Brynjolfsson and Mcafee 2017). This process is rooted in supervised learning systems, where a machine is trained to predict a particular result based on a diverse range of inputs provided by large databases. Notably, the progress in machine learning is intricately tied to big data,[36] and a pivotal development in

[33]For a comprehensive review of IoT uses in different sectors seeAndreoni et al. (2021).

[34]The Apache Software Foundation (ASF) is a non-profit organization that provides open-source software.

[35]There is a strong link between the big data and AI and Web 2.0 life cycle, which has to do with the fact that these platforms were developed by social media companies, e.g. BackType which developed Apache Storm and LinkedIn which developed Apache Samza.

[36]Simultaneously, for big data analytics to evolve, machine learning is a key element. This underscores the high degree of *interdependence* between these sets of technologies.

the early 21st century has been the creation of new algorithmic techniques. These techniques enhance predictive power by utilizing backpropagation with multiple layers, in conjunction with vast datasets (Cockburn et al. 2018). Some examples of current applications are, for instance, in the medicine field, where machines now make disease diagnoses with higher accuracy than humans (Frey and Osborne 2017). Another application is in legal activities, where computers scan and process a wide range of legal documents necessary for a trial or pre-trial procedure (Frey and Osborne 2017). These examples highlight that artificial intelligence is capable of handling cognitive non-routine activities.

Overall, the adoption of AI among firms remains relatively low. Between 2016 and 2018, the percentage of firms using or testing AI in the U.S. was reported to be 3.2% (Acemoglu et al. 2022). Furthermore, research indicates that adoption tends to be more prevalent among larger and older firms (Zolas et al. 2021, Acemoglu et al. 2022).