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

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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 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.

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

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1 Introduction

As automation technologies increasingly codify tasks, they hold the potential to displace workers who perform them, consequently diminishing the demand for such jobs (Simon 1960; Autor et al. 2003). However, the existing literature also indicates that, over the long term, short-term changes in labor demand due to task codification are likely to be offset. This compensation can occur through enhanced productivity (Aghion et al. 2022), increased final demand (Vivarelli 1995), or the creation of new tasks (Autor et al. 2022). A critical question is to what extent automation technologies impact labor markets in the short term, whether the impact differs across different vintages, and during different phases of adoption of each vintage.

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, leading to the emergence of technology life cycles (Tushman and Anderson 1986). These cycles begin with rapid developments in various configurations and applications, culminating in the establishment of a dominant design (Abernathy and Utterback 1978). The standardization of the technology is followed by a period of incremental changes and widespread adoption, and then by a decline in both innovative activity and adoption rates, paving the way for the next breakthrough innovation and subsequent life cycle. The diffusion pattern of the breakthrough technology mirrors this cycle: following the establishment of the dominant design adoption grows exponentially, to slow down as the diffusion of the technology reaches and surpasses the midpoint of potential adopter saturation (Geroski 2000).

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

2021).[1] For instance, mechanical automation, robotic automation, and intelligent robotics perform different tasks with varying abilities and connectivity within an 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: firms seek technicians (Lewis 2020); the retraining of existing workers is costly and time-consuming (David 1985); and firms reconfigure the organization of production (Ciarli et al. 2021, Battisti et al. 2023), including the division of labor (Langlois 2003). Whereas in the final stages of the life cycle, the technology is mature, more standardized, and firms have learned to integrate it efficiently into the production process, even to perform tasks previously done by workers.[2] In the second scenario, early adopters may replace workers. This could be because early adopters are the most productive and technologically advanced firms, capable of rapidly integrating new technologies and replacing workers. Adoption, in turn, may lead to production expansion, potentially increasing worker demand during the more mature stage of the technology life cycle (Vivarelli 1995). Ultimately, which scenario prevails is likely to depend on the specific technology and breakthrough technology involved.

In this paper, we study the impacts of different groups of technologies and the phases of their life cycles on regional employment. We empirically examine which effect prevails across 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 for measuring investment in information and communication technologies and software and databases (Release 2021); the International Federation of Robotics (IFR) to measure investment in robots; and ARDECO for assessing labor market outcomes (Release 2021).

Our analysis proceeds in two stages. In the first stage, we identify technology life cycles

[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."

from 1995 to 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, corresponding to fluctuations in technology investment. Notably, we identify three concurrent life cycles for CT, IT, and SDB, reflecting the main digital eras in ICT since the 1990s: the World Wide Web 1.0 era (1990–2004), the Graphical User Interface and Cloud Computing era (2004–2012), and the Big Data and AI era (2013–).

In contrast, the analysis reveals a single, extended technology life cycle for robots spanning from 1995 to 2012. This aligns with advancements in industrial robots, particularly in enhancing their articulation and mobility capabilities through sensors. Since 2013, a second cycle in robotics has emerged, coinciding with breakthroughs in Big Data and AI that also mark the ICT and SDB cycles.

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

To determine the effects of regional exposure to each technology, we adopt a shift-share instrumental variable (IV) approach, a method 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.

Furthermore, by categorizing regions based on their productive structures and productivity levels in 1980 (i.e., before our analysis period), we investigate whether the impacts of these technologies vary according to regional characteristics. This exploration spans different technologies and their respective life cycle phases.

Our 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, short-term negative impacts of ICTs and SDB on regional employment-to-population ratios within their technology cycles dissipate in the long run. With robots, the alternating positive and negative short-term effects across different phases of their technology life cycle nearly balance out, resulting in a minimal long-term positive effect. This observation aligns with existing literature that suggests varied 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, as evidenced by the average reduction in the employment-to-population ratio by 1-2 percentage points annually during various phases of ICT investment.

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

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

This pattern is not evident with robots. Contrary to ICT and SDB, during robots' third phase of the first cycle, characterized by technology maturity, lower prices, and a slowdown in investment rates, regional employment and the employment-to-population ratio increases, which may suggest that adopters experience an increase in sales.[3]

Fourth, we find that the impact of automation on employment is more influenced by the phase of the technology life cycle than by regional structural differences, such as sector specialization and productivity. While the magnitude of automation's impact varies among regions with different levels of productivity or labor specialization, the direction of the impact remains consistent across these regions. But it does vary significantly across different phases of the technology life cycle for all regions. This finding underscores the dominant role of the technology life cycle phase in shaping the labor market effects of automation, transcending regional structural variations.

This paper contributes to an extensive body of literature that examines 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 predominantly focus 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). Regarding Europe, findings are more varied: Acemoglu et al. (2020) report negative employment impacts of robot investment, while (Dauth et al. 2021) find no significant effect, and (Reljic et al. 2023) observe a positive impact. Further, studies

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

that differentiate among robots, communication technologies, information technologies, and software and databases report mixed effects, which vary based on the specific technology and industry involved (Blanas 2023; Jestl 2024). Additionally, 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 between 2005 and 2015.

We contribute to this literature in two ways. Firstly, we introduce a novel technology life cycle perspective to the analysis of labor market adjustments in response to automation. Previous research often differentiated short-term effects of automation technologies based on arbitrary time periods that encompassed several technological breakthroughs. Our approach, however, delves into shorter-term dynamics defined by the specific life cycles of each of the four groups of automation technologies: robots, CT, IT, and SDB. This perspective allows for a more nuanced understanding of how labor markets adjust to technological advancements within distinct phases of technology development.

Secondly, we contribute to the literature by investigating how the impacts of automation technologies on labor markets may vary among regions with different initial productivity levels and industrial 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 labor market impacts differ more significantly between technological breakthroughs than between regional characteristics. This highlights the importance of technology life cycles in shaping labor market outcomes, underscoring the need to consider the specific stages of technology development when assessing automation's effects.

The paper is structured as follows. Section 2 presents a detailed description of the main variables and the databases used in our analysis. Section 3 identifies the technology life cycles and outlines the primary innovation breakthroughs for robots, ICT, and software and databases. In Section 4, we elaborate on the empirical methodology, including our instrumental variable strategy. Section 5 delves into the results, examining the effects of automation technologies throughout their respective technology life cycles and discussing the principal regularities we have uncovered. Finally, 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 for the period 1995 to 2017. The 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. These variables are constructed using data from the ARDECO database at the NUTS-2 level.

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

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

Exposure to automation technologies. We consider four automation technologies:

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

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

[4] Our analysis is restricted to this set of countries, thereby excluding Eastern European countries, for two methodological reasons. Firstly, data on the initial sectoral employment shares in 1980 are required to measure the technology exposure of European regions within our shift-share design. For some countries, these employment shares are not available in 1980. Secondly, a balanced panel of technology stocks is necessary for the period 1995–2017 to identify investment cycles in automation technologies. An unbalanced panel would bias the identification of these cycles towards the subset of countries with data available up to 1995, whereas our objective is to assess the impact of exposure to automation technologies across the entire set of countries.

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

We consider Computer Software (4a) and Database (4b) as one technology due to data availability.

We employ the number of robots in use (i.e., robot stock) in each sector at the country level, sourced from the International Federation of Robotics (IFR); refer to Jurkat et al. (2022) for a comprehensive review. Robots are present in only three out of six sectors: Industry (B-E), Construction (F), and Non-Market Services (O-U). Considering that approximately 30% of the robots are unspecified (i.e., not assigned to any sector), we proportionally distribute them across sectors based on the sectoral share.[5] Additionally, for some countries (such as the US), where robots are not available at the sectoral level for certain years, we estimate them by distributing the total number of robots weighted by the average sectoral share from years with available data.[6]

The data on ICT and Software and Databases are retrieved from the EU-KLEMS database (Release 2021). We capitalize on the fact that this database distinguishes between these technologies. Consequently, we analyze the stock of communication equipment (i.e., communication technology), computing equipment (i.e., information technology), and computer software and databases (i.e., software-database) at the country-industry level. Our measures for these technology stocks are the net capital stock (expressed in 2015 volume terms), derived from national accounts.[7][8] Since the EU-KLEMS data is in national currency, we convert the figures for non-euro countries into euros using the nominal exchange rate from EUROSTAT.[9]

We categorize sectors according to the NACE Rev.2 classification. Due to a classification shift from Rev. 1.1 to Rev. 2 in 2008, we aggregate sections to ensure consistent sector

[5] Specifically, we calculate the ratio of the number of robots in each sector to the total number of robots that are effectively assigned to sectors. We then allocate the unspecified robots using these ratios. While some studies do not distribute unallocated robots across sectors (see Graetz and Michaels 2018, Dauth et al. 2021), in our analysis, it is more reasonable to do so to ensure a harmonized series of robots that is comparable when aggregating our measure of technology exposure across sectors.

[6] Our approach is as follows. Suppose, for a specific country, sectoral robot stock data is missing from 1995 to 2000. We calculate the average sectoral shares from 2001 to 2017 and then impute robots for the earlier years by applying these estimated shares to the total robot count.

[7] Using investment would have been preferable, due to small difference in accounting for depreciation across national statistical offices. However, for the IFR data for robots we face the opposite problem that flows (robot installations per year) are inconsistently tracked across countries, due to the different compliance rules explained in Jurkat et al. (2022). Because the inconsistency with robots flow data are significantly more problematic than those on investments in EU-KLEMS, we choose to use stocks.

[8] For Ireland, the technology stocks are available at the country level but not at the sectoral level. Therefore, we estimate them by allocating the country-level technology stocks to the respective sectors within the country, using the sectoral share in Ireland's gross fixed capital formation.

[9] This conversion applies to Denmark, Sweden, and the United States (which is used as an instrument).

representation; see section A.1 in the appendix for detailed information on the harmonization of sectors.

Control variables. To account for other factors that may influence regional labor market outcomes, we incorporate two control variables 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.[10] Second, we consider the potential impact of trade and international competition by controlling for imports from China, as recorded in the OECD Trade in Value Added database.[11] The growth in trade with emerging countries has been shown to have adverse effects on employment in manufacturing (Autor et al. 2013, Dauth et al. 2014, Autor et al. 2015). Both control variables are calculated at the regional level.

Instrumental variable. To address the endogeneity in the relationship between decisions to invest in automation technologies and labor market outcomes, we use investment data in similar automation technologies in the U.S. as an instrument for investments in European regions. This data is obtained from the IFR (for robots) and EU-KLEMS (for ICT, software, and databases).[12] In constructing our instrument (detailed in Section 4), we normalize the technology stock using sectoral employment data from 1980, sourced from the OECD Labor Force Statistics.[13]

3 Technological Breakthroughs

Innovations in Information and Communication Technologies (ICTs), like all technologies, tend to cluster temporally around major breakthroughs (Silverberg and Verspagen 2003), which initiate a series of incremental innovations before leading to the next major advancement.

In this section, we qualitatively identify the primary innovation breakthroughs for robots, communication technology, information technology, and software and databases since 1990. This identification combines insights from both innovation studies and engineering literature. Then, we analyze the diffusion of these breakthroughs across Europe over time, examining

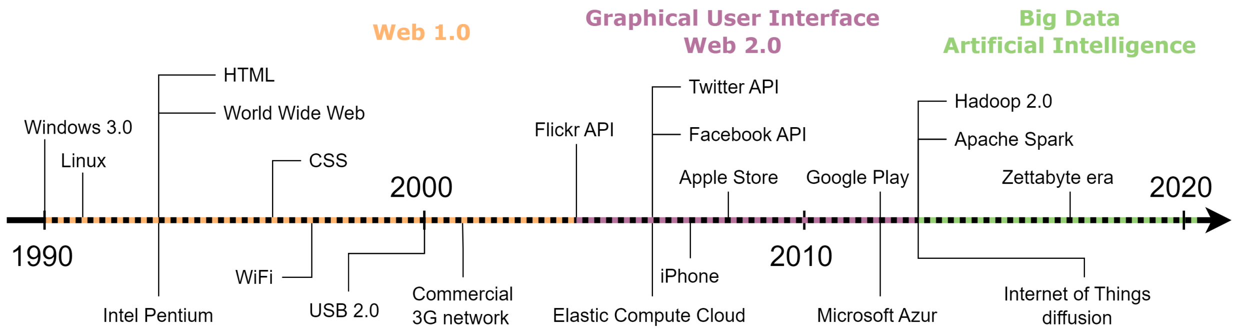
[10] OECD (2021), OECD Inter-Country Input-Output Database, http://oe.cd/icio. Release: November 2019.

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

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

[13] OECD (2022), OECD Annual Labour Force Statistics (ALFS), https://stats.oecd.org/.

Figure 1: Main digital technology innovations since 1990



Notes: This figure presents the main digital technology innovations since 1990. The three digital technological cycles are the Web 1.0 cycle (from 1990 to 2004), the Graphical User Interface and Web 2.0 cycle (from 2005 to 2012), and the Big Data and Artificial Intelligence cycle (since 2013).

the investment trends in robots, communication technology, information technology, and software and databases. For each of these four technology categories, we differentiate between periods of investment acceleration (early adoption of the new technology) and deceleration (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, is characterized as "a set of interrelated radical breakthroughs, forming a major constellation of interdependent technologies" (Freeman and Perez 1988, Perez 2010). Following Nuvolari (2020), we identify four major interdependent technological components of ICTs: electronic components, computational power (semiconductors and computers), software, and networking equipment. Radical advancements in these components can lead to significant innovations in ICTs. The development of microprocessors was central to the ICT revolution, enhancing the computational capacity of electronic devices such as computers while reducing their cost (Freeman and Louçã 2001).

Since the advent of microprocessors, there have been significant advancements. Figure 1 presents the main digital technology innovations since the 1990s, pinpointing three major radical shifts in various ICT components (breakthroughs): Web 1.0 (1993–2004), Graphical User Interfaces (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–). The reduction in size and cost of microprocessors, significantly increasing the adoption of personal computers, and the introduction of user-friendly operating systems like Windows 3.0 and Linux during the 1990s, led to the widespread adoption of computers (IT). The emergence of the World Wide Web in 1993, alongside these technical changes, facilitated the Internet's adoption (CT) by businesses (e.g., e-commerce) and end-users. While software development played a crucial role in disseminating ICTs to end-users in the 1990s, notably with Windows 3.0, investments in databases remained limited.

Graphical User Interface and Cloud Computing (2004–). The second technological breakthrough is marked by the emergence of Web 2.0 technologies in the early 2000s, following significant advancements in Graphical User Interfaces (GUI) and cloud computing. Previous developments in digital infrastructure (i.e., the Internet and mobile communication) also spurred the creation of user-friendly devices like smartphones. This era began a phase of significant network economies (Mansell 2021) and the proliferation of new service applications (e.g., social media, electronic commerce, search engines, and data analytics). During this period, 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 Artificial Intelligence, driven by heightened investments in neural networks and deep learning. Enabled by the growing availability of large data sets, known as Big Data, and the advancement of machine learning and deep learning algorithms, coupled with a rapid increase in computational power (building on cloud computing), this research has accelerated. Significant enhancements in network and communication technologies have also facilitated the spread of the Internet of Things (IoT).[14]

3.2 Robot Breakthroughs: From Industrial Robots to Robotics

Advancements in ICTs, software, and databases also laid the foundation for the evolution of industrial robots.

Industrial Robots (1990–). The development of robotics in the 1990s built upon the three main technologies integral to the third generation of robots (1978–1999), as identified by Gasparetto et al. 2019. These technologies include: remote and self-programming capabilities enabled by microprocessors, sensors, and rudimentary 'intelligence' for diverse condition

[14]IoT is typically defined as a suite of technologies that 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, this technology is a major source of data generation, propelling advancements in artificial intelligence.

responses and environmental interaction (e.g., visual or tactile inspection and servo controls), and the capability for six-axis movements (also discussed in Savona et al. 2022). Moreover, the advancement of communication protocols in the 1990s, such as the internet, the World Wide Web (WWW), and later wireless technologies, further expanded control capabilities and spatial movements, leading to the emergence of mobile robots (Grau et al. 2017).

Robotics (2010–). A significant shift in robotics has been driven by technologies integral to the evolution of ICTs, software, and databases. Advances in AI technologies, in conjunction with IoT and sophisticated sensors, have paved the way for intelligent computing systems. Enhanced sensors and improved wireless communication technologies have enabled complete mobility on manufacturing floors and self-coordination among swarms of devices (IoT). These radical developments have augmented the autonomy of robots, their ability to collaborate with humans, and their precision in various industrial applications (Müller 2022).

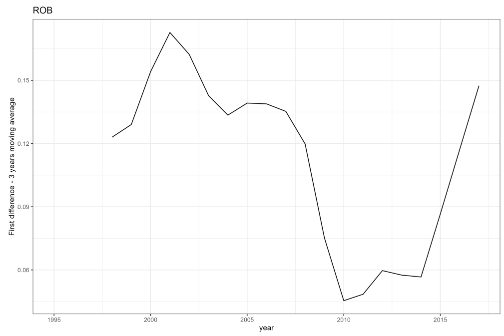
In summary, for the period covered in this paper (1995–2017), we identify three primary developments (breakthroughs) in ICTs and two main advancements in robotics. In the realm of ICTs: the evolution of Web 1.0 technologies and software, alongside a decrease in computing costs and rapid advances in user-friendly software (1990–onwards); the emergence of Web 2.0, graphical interfaces, simplification of data acquisition technologies (e.g., APIs), cloud computing, and storage (2005–onwards); the AI revolution, accompanied by the connectivity revolution (IoT) (2013–onwards). In the domain of industrial robots: enhancements in flexibility, control, and sensing capabilities during the third generation of robots (1990–onwards); followed by the advent of the fourth generation of intelligent robots, also leveraging developments in AI (2010–onwards).

3.3 Technology life cycles in ICT and Robots

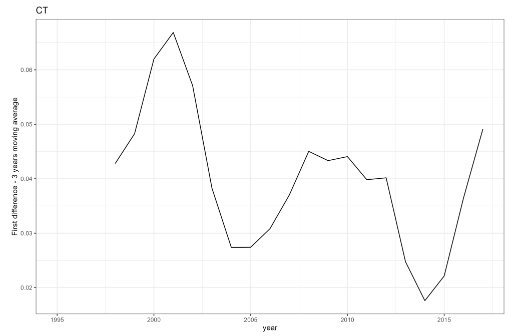
We next examine investments in robots, communication technology, information technology, and software and databases since 1990, both before and after the innovation breakthroughs identified previously. Our goal is to determine whether the investment pace changes throughout each breakthrough's life cycle—typically accelerating adoption following a breakthrough and decelerating before the next one.

Given our objective to trace the life cycle of these technologies, and considering the lack of detailed information on the adoption of specific technologies within each category and by country, we analyze investment patterns aggregated at the European level. For each category of automation technologies, we aggregate the investment stock (per thousand

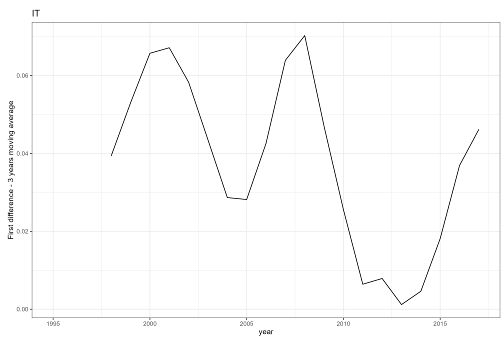
Figure 2: Evolution of technology investment in first difference (3-year moving average)



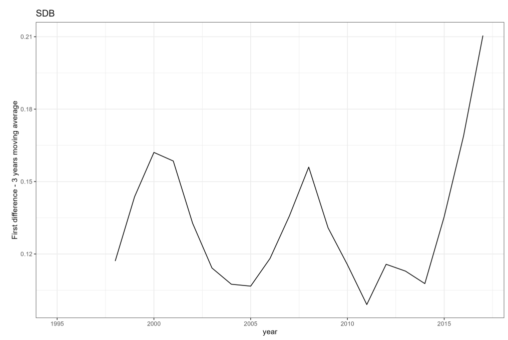
(a) Robots



(b) Communication technologies



(c) Information technologies



(d) Software and database

Notes: This figure shows the evolution of the difference first difference in each technology (robots, communication technology, information technology, and software and database) per 1000 workers at the EU level (representing the aggregate data for the 12 European countries in the sample). The series have been smoothed by taking the 3-year moving average.

workers in 1980, in constant prices) across all European countries.[15]

As expected, investment in the four categories of automation technologies has increased annually since 1990 (see Figure D.9 in Appendix B). To assess the rate of increase, we calculate the first difference in the time series (after applying a three-year moving average to smooth short-term fluctuations). Figure 2 illustrates changes in investment for robots (2a), communication technologies (2b), information technologies (2c), and software and databases (2d).

The patterns of investment in ICT and software–database from 1995 to 2017 exhibit three phases of acceleration and deceleration, with remarkably similar timing across the three groups of technologies. Following the Web 1.0 breakthrough in the early 90s, we observe an investment acceleration phase lasting until around 2001, succeeded by a declining

[15]Since the technology stocks are calculated in volume terms, they are not directly additive. Therefore, we adhere to the EU-KLEMS methodology for generating aggregates (EUKLEMS&INTANProd 2021). Namely, we calculate the aggregation at the European level at both current and previous years' prices. Subsequently, we derive the volume index (at the European level), which is then used to chain-link the values using 2015 as the base year. Finally, we normalize the series by the employment aggregated at the European level in 1980.

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: This table summarizes the years of each phase of the technology life cycles for communication technologies (CT), information technologies (IT), software and database (SDB), and robots, as derived from 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 rate.

rate of change until approximately 2004/5. This period coincides with the emergence of the second breakthrough in our timeframe: the graphical user interface and cloud computing. Post this breakthrough, investment once again accelerates, continuing until between 2008 and 2011—varying with the technology group—after which the rate of change enters a phase of decline until the next breakthrough around 2014: Big Data and Artificial Intelligence. From 2014 onwards, a third technology cycle begins, with all three technologies experiencing an ongoing increase in investment change as of 2017.

Investment in robots, however, follows a distinct trajectory. During the first cycle, we note an acceleration until 2001, followed by shorter cycles until 2007, indicative of a prolonged phase of high, albeit diminishing, adoption rates. This period of relatively stable investment growth then transitions into a deceleration phase, lasting until the Robotics breakthrough—Big Data and Artificial Intelligence. Since 2013, the onset of this second technology lifecycle for robots is observable, continuing as of 2017. Table 1 summarizes the phases of the technology life cycles that we use to determine the define the sub-period for estimating the impact of investment in the four group of technologies on regional labor markets.

The investment patterns in robots, ICTs, and software and databases in Europe—which diverge from the cycles in aggregate consumption (refer to Figure D.8)[16]—qualitatively indicate a technology lifecycle characterized by increasing adoption rates following each breakthrough in various components of these technologies, and decreasing rates prior to the next breakthrough. While specific data on technology adoption in individual countries is unavailable, these trends, coupled with the discussions in Sections 3.1 and 3.2, imply distinct phases in the evolution and use of ICT and robots, potentially leading to varying impacts on the labor market.

4 Empirical Specification

Having delineated various technological breakthroughs in ICT and robotics, as well as their respective lifecycles, we now proceed to evaluate the impact of investment in IT, CT, SDB, and robots on regional labor markets in Europe. We consider the lifecycle of each technology as an inherent characteristic and thus assume that each region is exposed to every phase of the technology lifecycle. Given that data on ICT and robotics investments are available at the country level, we calculate technology exposure (i.e., the change in technology stock) as a shift-share instrument across different phases of the technological cycles. Then, we introduce our baseline model for estimating labor market adjustments in response to technology exposure throughout these cycle phases. Finally, we address identification challenges and outline the IV strategy, which relies on using U.S. technology investment as an instrument for European technology investment.

4.1 Shift-share technology exposure in technological investment phases

We first measure the exposure of a European region r to technology K between a year 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,

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

[16] This was also verified by regressing the investment time series for each technology group against a linear time trend and real consumption per thousand workers in 1980 (aggregated at the European level). The findings are presented in Figure D.9 in Appendix D. The second panel shows the residuals after regressing the time series on a linear time trend, while the third panel of Figure D.9 displays residuals after including both the time trend and real consumption.

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.[17]

As we segment the period from 1995 to 2017 into sub-periods, representing the different phases of the technology life cycles, it is necessary to adjust our shift-share design accordingly.

Consider the year $t + h'$ as a breakpoint—i.e., any intermediate year between 1995 and 2017—that delineates two phases. We can divide the exposure, as defined in Equation (1), into two parts: 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 terms and referencing the exposure definition from Equation (1), we can express the total exposure as the sum of the exposures of 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:

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

Similarly, we consider labor market adjustments over the different phases of technological investment. The division for this 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 deceleration, τ, as identified in Section 3.3. These phases vary

[17] Consequently, our change in exposure is confined to changes in the technology stock. We maintain the weights —i.e. the sectoral share of employment in the region— constant and take the value for 1980 to avoid endogeneity issues.

depending on the technology, as the technological cycles do not perfectly align. 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 technology K throughout the various phases $\tau \in \mathcal{T}_K$ of each technology's life cycle, we use the following model:

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

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

We standardize the technology exposure at the phase level to facilitate comparisons of effect magnitudes across different technological phases and to enhance the interpretability of the coefficients. Consequently, 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 the level of employment and the average wage are both calculated as log-changes, allowing coefficients to be interpreted as percentage changes. Meanwhile, changes in the employment-to-population ratio and the wage share are computed directly, so coefficients here can be interpreted as changes in percentage points.

4.3 Identification and IV strategy

The relationship between investment in automation technology and outcomes in employment and wages is endogenous. Decisions to invest in automation technologies are influenced by labor cost and availability (Bachmann et al. 2022), including factors stemming from labor market institutions (Presidente 2023). Furthermore, some shared determinants of automation and labor, such as labor institutions at the industry-region level, are not directly observable. While controlling for real consumption (as a proxy for demand shocks) and trade exposure partially mitigate this issue, it does not fully address it.

Measuring automation technologies presents several challenges. Firstly, not all robots in the IFR data are allocated to specific sectors. Secondly, methods for measuring and accounting for tangible and intangible capital, such as ICT and software, differ across countries and over time.

Consequently, estimates derived from Equation (3) are likely biased. The bias direction depends on the prevailing source of endogeneity.

Following the instrumental variable strategy used in Acemoglu and Restrepo (2020) and Antón et al. (2022), we use technological investment data from another country undergoing significant automation, the United States.[18]

We construct the exposure of European regions over a period by measuring the change in automation technologies in the US (shift) over the same period, while 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 technology that may influence diffusion in a country similar to Europe. We proportionally allocate the investment according to the exposure of each region in 1980, based on their sectoral specialization.

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

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

where $Exposure_{r,\tau}^{K,EU}$ is the baseline exposure to technology K in 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.

For the productive structure, we employ a k-means algorithm, using regional employment

[18] An alternative approach in the literature is to use data from other European countries (Aghion et al. 2019, Dauth et al. 2021, Bachmann et al. 2022). However, employment trends in EU countries are more closely correlated, particularly due to global value chains (GVCs) and human capital flows, than those between EU countries and the US.

shares in 1980 across three broad sectors—Agriculture, Industry, and Services—as clustering variables.[19] Our preferred specification identifies three distinct groups of regions: agriculture-intensive, industry-intensive, and service-intensive.[20]

To proxy for technological capabilities, we use regional labor productivity in 1980, classifying regions as high or low productivity based on whether their productivity level is above or below the median for the entire sample of regions.[21] Data are sourced from ARDECO.

5 Labor Market Impacts of Different Technology Vintages

In this section, we examine the labor market impacts of exposure to technology during different phases of the life cycles of each technological breakthrough. Our findings are based on the IV estimates presented in Tables C.2 to C.9 in Appendix C.[22] We aim to discern whether the cyclical pattern of emergence and adoption of digital automation technologies has influenced labor market impacts between 1995 and 2017 by comparing results across technologies and their life cycle phases. We first assess the differences between long-term and short-term effects. Then, we explore patterns in how digital automation technologies have affected employment and wages in European regions throughout technology life cycles from 1995 to 2017.

5.1 Short-term *versus* Long-term impacts

Significant short-term impacts of digital automation technologies on the regional employment-to-population ratio are evident in Tables C.6 to C.9. However, these effects are not sus-

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

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

[21]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 is unavailable, we have used 1995 data for these calculations. Figure D.3 displays the distribution of regions by productivity level relative to the overall sample of regions.

[22]Tables C.2 to C.5 provide the coefficients from the shift-share IV estimation. Tables C.6 to C.9 detail the coefficients for each regional cluster, estimated separately to highlight heterogeneity in the relationship between the primary variables. To account for the type of cluster and productivity level, we interact the technology exposure K with a slope dummy indicating the cluster and productivity level respectively. In other words, we perform separate regressions for both clusters and productivity categories, thereby enhancing the granularity of our analysis. Tables C.10 to C.13 contain the OLS results.

tained in the long term (Table C.1), except for robots, where long-term impacts are notably smaller.[23]

For the entire period of 1995–2017, the long-term impact of ICT and SDB on the employment-to-population ratio is negligible and statistically insignificant (Table C.1, third column). This overall minimal effect masks significant labor market dynamics during shorter investment cycles, as indicated in Tables C.4–C.5.

For instance, IT exposure results in both positive and negative regional changes in the employment-to-population ratio, contingent upon 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.

In essence, for the long-term period of 1995–2017, European regions seem to balance out the predominantly negative short-term effects of ICT and SDB exposure on the employment-to-population ratio. Various mechanisms potentially mitigate both negative and positive short-term impacts of automation technology investments over time.

Robots demonstrate a different pattern compared to ICT and SDB in two key respects. Firstly, 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, totaling 1.54pp between 1995-2017 (Table C.1). However, this increase is lower than the sum of the average impacts observed for different phases of the robot life cycles (Table C.2). Secondly, positive impacts on employment-to-population ratio dominate negative impacts in the case of robots, unlike 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 discrepancies reported in previous studies regarding the impact of robots on regional employment in European countries. Combining the first two phases of the industrial robots life cycle (1995–2002 and 2002–2006) reveals a negative impact on employment, aligning with Antón et al. (2022) findings of a negative effect for 1995–2005 but positive for 2005–2015. Our results suggest that variations in past studies' findings may be attributed to the specific technology phases included in their analysis periods.

The long-term impact of IT and SDB on average regional wages from 1995 to 2017 is minimal and not statistically significant (Table C.1). Unlike the employment-to-population ratio, this lack of significant impact is consistent across most short-term periods. Notable

[23] We focus on the employment-to-population ratio to consider the impact of technology investments on population changes, including due to migration.

wage impacts were observed only during the life cycles of Web 1.0, a period characterized by the widespread adoption of personal computers with user-friendly software (Tables C.4 and C.5).

CT differs from IT and SDB in its impact on wages. The positive effect of CT on average wages, also limited to the Web 1.0 life cycle, yields a notable annual increase. Regions investing 1-STD more in CT during this period experienced wage increases of 0.24% and 0.99%, and these gains are sustained in the long term (Table C.1).

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 in robots than the average experience an annual wage decrease of about -0.26%, totaling -5.72% over the entire period. This long-term impact, however, is less pronounced than the sum of the short-term impacts observed between 1995 and 2006, 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

Analyzing data from Tables C.2 to C.9, we identify four key findings regarding the role of technology life cycles in influencing the impact of automation on regional labor markets.

Firstly, the impact of exposure to automation technologies on the employment-to-population ratio varies among different technological breakthroughs within the same group. It suggests that different technologies within the same group (e.g., Web 1.0 vs Web 2.0 for IT) can have distinct impacts. Combining several technological breakthroughs in a single estimation may yield results that amalgamate these diverse, and potentially contrasting, effects.

Secondly, focusing on the second technology life cycle (GUI and cloud computing), which is the one that our data captures more accurately, we find that negative short-term impacts on the employment-to-population ratio are predominantly observed in their later phases. This life cycle combines enhanced, flexible computational capacity (cloud computing) with technologies that improve coordination and labor division along value chains (Web 2.0 and graphical user interfaces). Results suggest that in the early phase of rapid technology adoption, firms in exposed regions tend to maintain employment levels (Domini et al. 2021), leading to an increase in the employment-to-population ratio. However, in later phases, when late adopters use more mature technology, investments replace labor, leading to reduced labor demand. Alternatively, the drop in the employment-to-population ratio in the second phase may result from early adopters that manage to optimize technology use and reduce their workforce. In both cases in the short term potential increases in sales or creation of new tasks do not compensate.

Thirdly, the effects of robot exposure on regional employment contrast with those of ICT and SDB. Similar to ICT and SDB, early adopters of robots during the initial phase experience an increase in the employment-to-population ratio due to labor hoarding. However, unlike ICT and SDB, also late adopters may benefit from sales increases in the technology's mature phase, leading to employment growth. The negative impact on employment is observed primarily during the intermediate phase, where the labor replacement effect outweighs compensatory mechanisms.

The contrasts between the impacts of robots and those of ICT and SDB indicate differing approaches by firms in integrating these technologies during various phases of the technology life cycle, meriting further investigation at the firm-occupation level. For instance, the integration of ICTs and SDB into production processes might lead to quicker worker replacement compared to robots.

Additionally, regional compensation mechanisms might explain these differences. For example, a limited number of firms adopting robots Deng et al. (2023) could potentially dominate the market at the expense of non-adopters. This market shift, coupled with worker displacement in adopting firms and reduced sales in non-adopting firms, could lead to an overall negative employment impact during the second phase. However, this trend might reverse in the third phase as late adopters join in, possibly benefiting from enhanced productivity and output.

Given that ICT, SDB, and robots are complementary (as discussed in Appendix E), the varied impacts across different phases of their life cycles might also suggest interplay among these investments, with some technologies replacing or complementing different tasks (Prytkova et al. 2024). Unraveling the mechanisms behind these differences necessitates a combined analysis of regional and firm data.

Fourth, regional differences in terms of industry specialization and initial productivity only marginally affect the results driven by the variations in technology life cycles. The vintage of automation technology and its phase of the life cycle are more relevant than sectoral and productivity differences among regions in explaining employment impacts from exposure to automation technologies. This conclusion is drawn from comparing regions with varying initial levels of sector specialization and labor productivity (measured in 1980) across different phases.[24] As reported in Tables C.6-C.9, the impact of technology investment on employment-to-population ratio and average wage is largely consistent across regions with different initial sector specializations and/or labor productivity levels, particularly in the

[24] See section 4 for details on the cluster estimation.

case of robots.[25] An exception to this pattern is IT investments, 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 examines the impact of labor market exposure to different vintages of four groups of digital automation technologies—robots, communication technology, information technology, and software and databases—across 163 European regions from 12 European countries. We focus on the short term impact during each phase of their technology life cycles from 1995 to 2017.

We identify key technological breakthroughs in each technology group and empirically validate them by analyzing investment trends in ICT and robots—periods of acceleration and deceleration. Then, we examine the effect of these technologies on labor market outcomes, including employment levels, the employment-to-population ratio, and average wages, across the two main phases of each technological cycle (acceleration and deceleration). The exposure of regional labor markets to each technology in its respective phase is quantified using a shift-share approach. Additionally, we employ an instrumental variable strategy, using technology investments in the US as a proxy for European investment in these four technology categories.

Our study delivers four main results. Firstly, although there are no effects of ICT and software and database on employment-to-population ratio in the long-run, we do observe significant positive and (predominantly) negative impacts in the short term, for each of the technologies life cycle. In practice, this means that, although increased demand, spillovers, and emergence of new tasks compensate the substitution effect of ICTs, workers do experience a reduced demand in the short run, particularly during the second phases of the technology life cycle when the technology is more mature. For robots, we find a long-term positive impact on employment-to-population ratio, quenched by smaller negative impacts in one of the phases. The short term results for robots help to explain the heterogeneous results documented in the literature so far. The differences between studies may arise from analyzing the impact of different vintages of robots, which we ind to have different impacts on the labor market.

Secondly, consistent with prior research, we find that the impact of the exposure to different automation technologies (like robots and ICT) on the labor market varies. Our

[25] 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.

findings extend this result, by showing that impacts also differ within the same technology groups, for different technological breakthrough.

Thirdly, we establish that the impact of technology exposure not only varies by the technological breakthrough but also by the different phases of each technology life cycle. The disparity between phases appears consistent across various ICTs, particularly when analyzing the technology life cycle that is more 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.

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

The primary implication of our study is that policies should focus also on the short-term effects of automation, which differ among technologies. While new jobs tend to emerge in the long run, accompanied by increased demand due to productivity gains and the introduction of new goods and services, the short-term impact requires policy intervention to support workers adversely affected by automation. Specifically, policies should aim to mitigate short-term negative effects on employment (as observed with ICT) and wages (particularly with robot exposure). 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, however, is not without limitations, which open avenues for future research. The primary constraint is the lack of data to observe technological adoption of specific technologies across countries. While we consider country-specific differences in exposure, our approach assumes uniform adoption of the same technology vintage across all European regions. Moreover, our analysis does not differentiate between early and late adopters within regions.

These limitations underscore the need for more comprehensive comparative studies across countries and regions, using comparable firm-level and employee data. Additionally, considering the varying impacts these technologies have on different worker types, it would be beneficial to supplement this analysis with a task-based approach. Such an approach could provide insights into whether varying technology life cycles significantly affect workforce composition.

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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.

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: 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.

B Descriptive Statistics

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

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).

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).

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.

C Additional Regressions

D Additional Figures

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

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.

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)

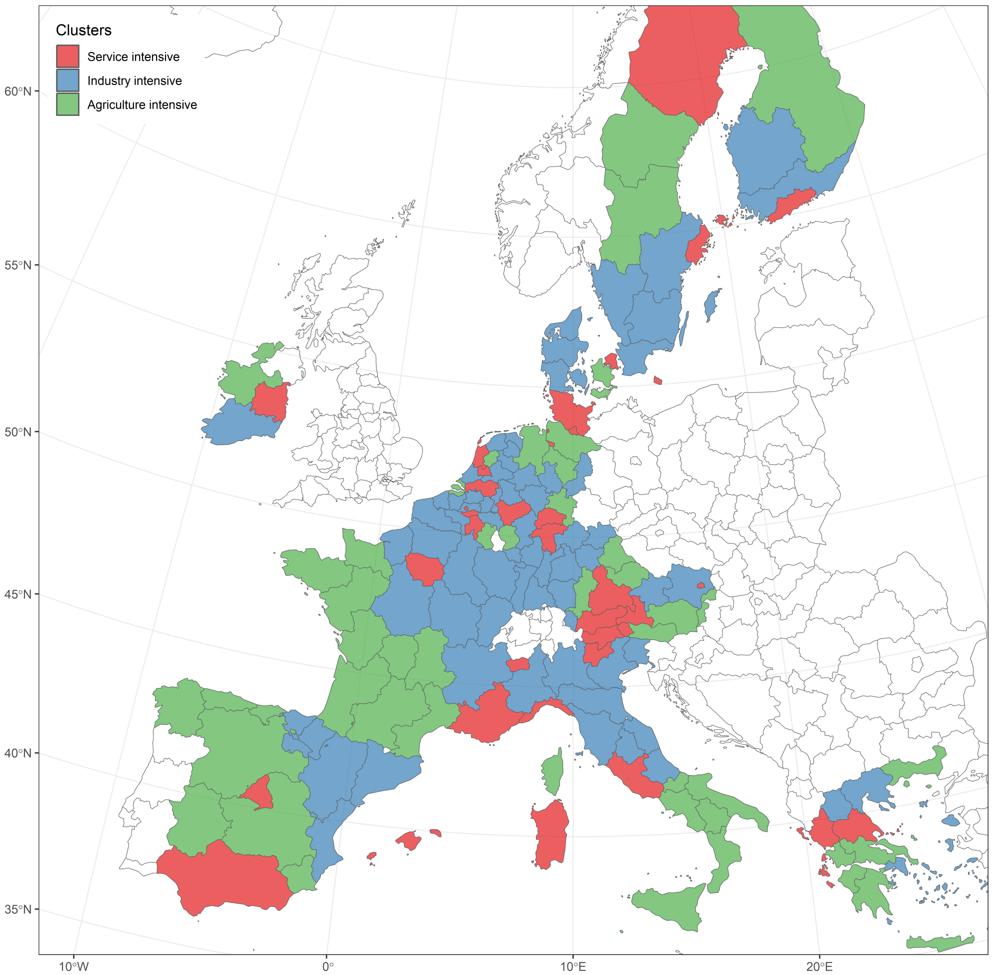
Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on IT exposure over the phases of the IT's life cycle in the different types of regions. The dependent variables represent 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)

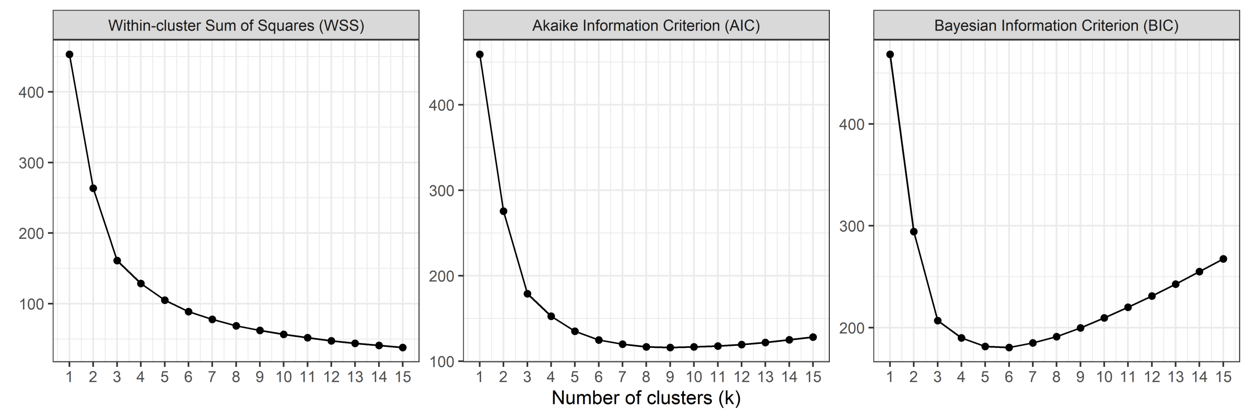
Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated IV-regressions of labor outcomes on SDB exposure over the phases of the SDB's life cycle in the different types of regions. The dependent variables represent 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.

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



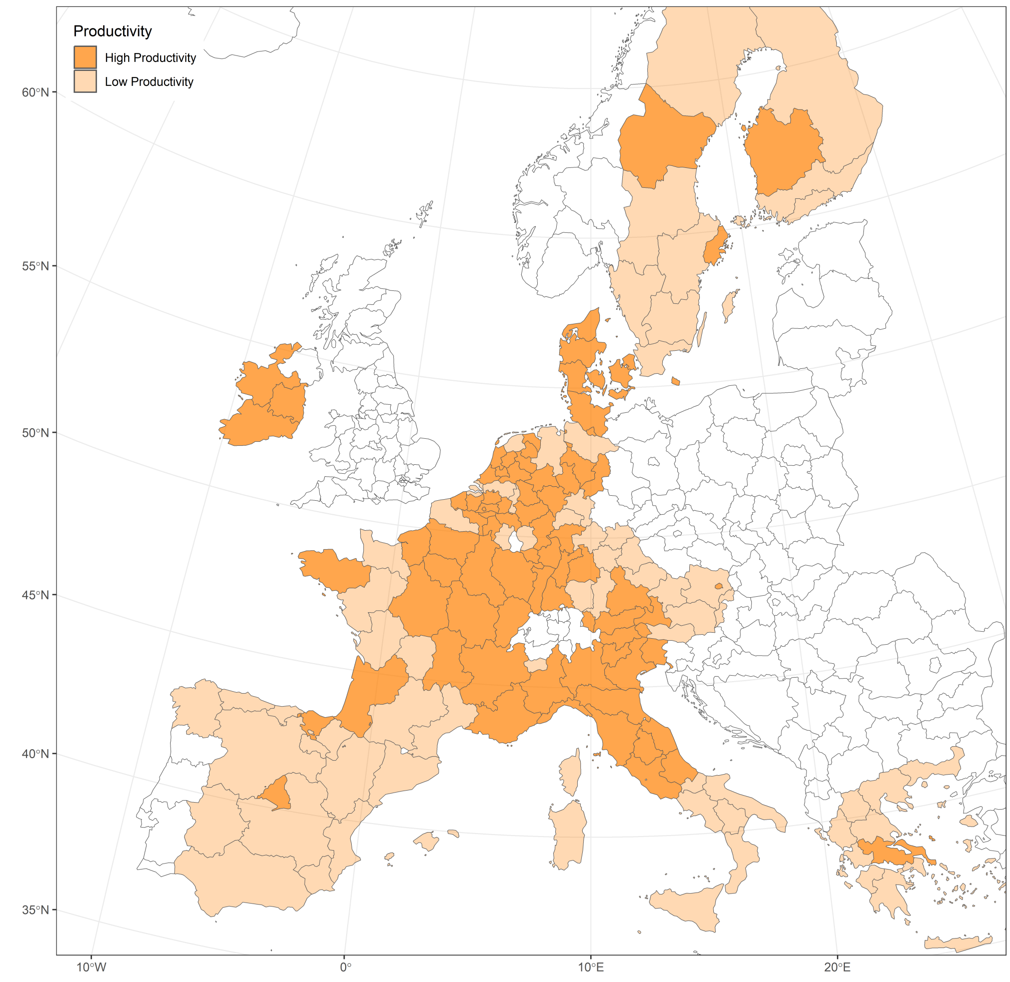
Notes: This figure presents the geographical distribution of the clusters. We compute the clusters by using a K-means algorithm. The variables employed for the clustering are the shares of employment in agriculture, industry, and services in 1980. We standardize the variables at the country level. The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

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



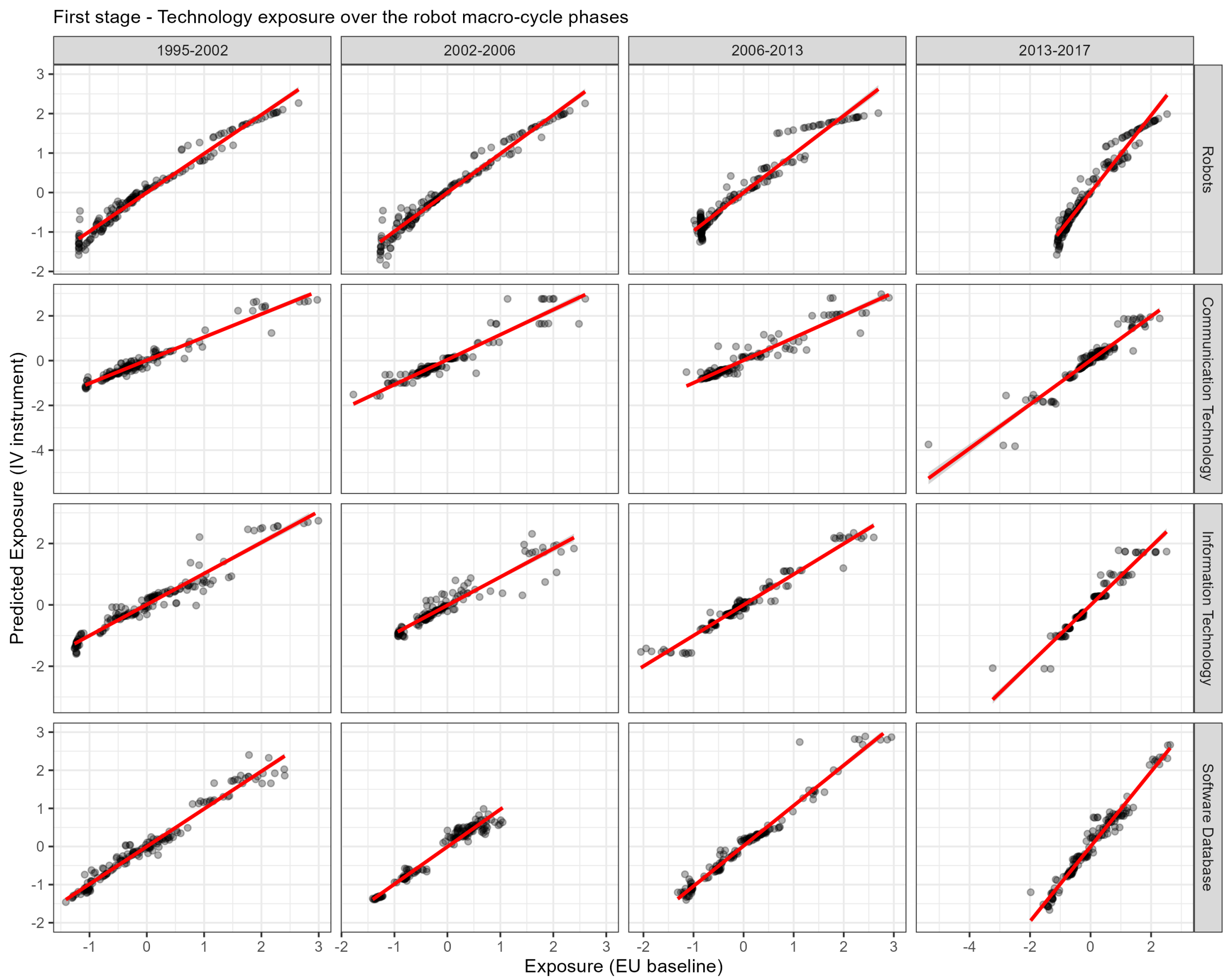
Notes: This figure presents the goodness-of-fit for a great number of clusters going from 1 to 15. We use three indicators to assess the goodness-of-fit: the Within-cluster Sum of Squares (WSS), the Akaike Information Criterion (AIC), and the Bayesian Information Criterion (BIC).

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



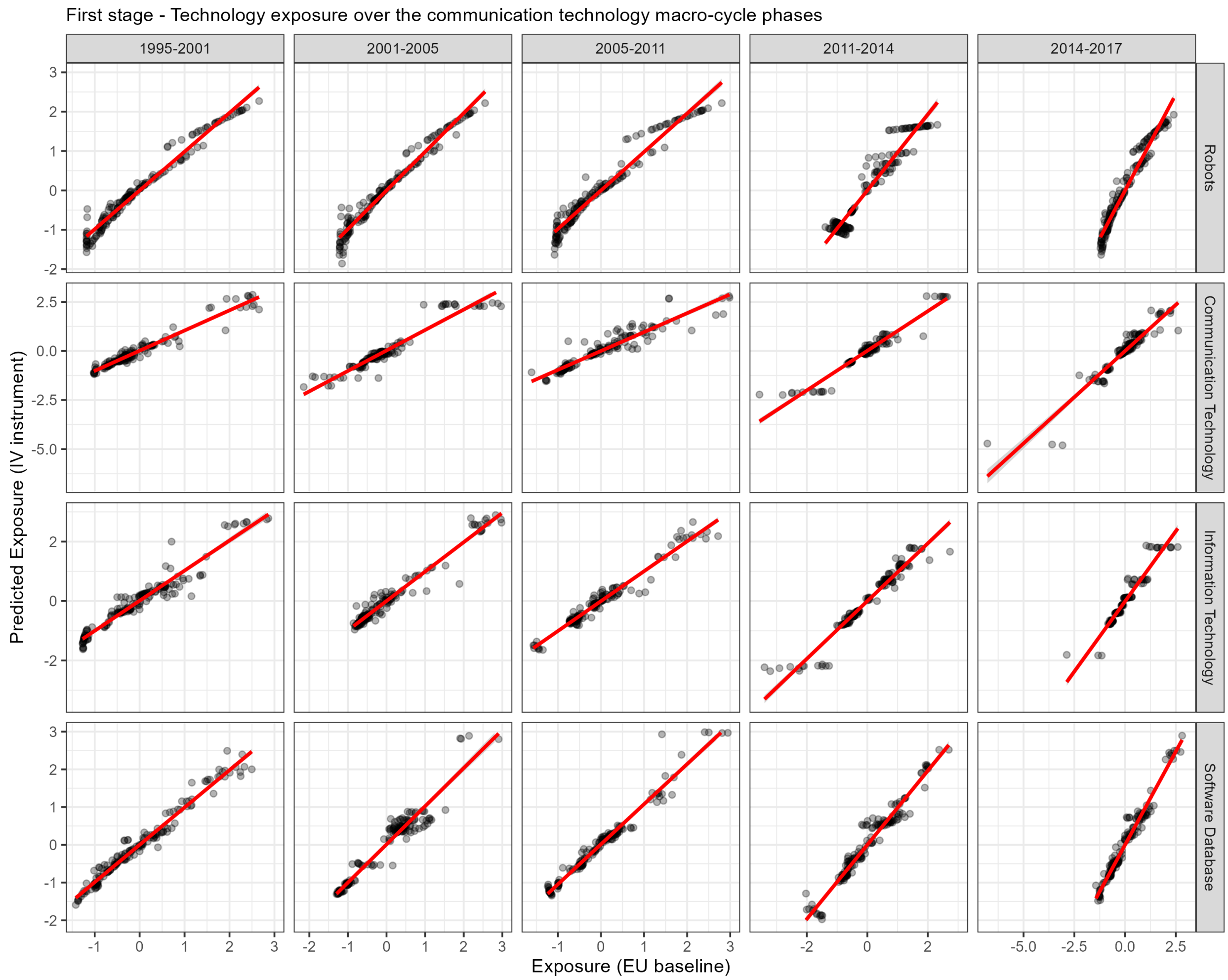
Notes: This figure presents the divide of regions according to their productivity level in 1980. We compute the clusters by using a K-means algorithm. The variables employed for the clustering are the shares of employment in agriculture, industry, and services in 1980. We standardize the variables at 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)



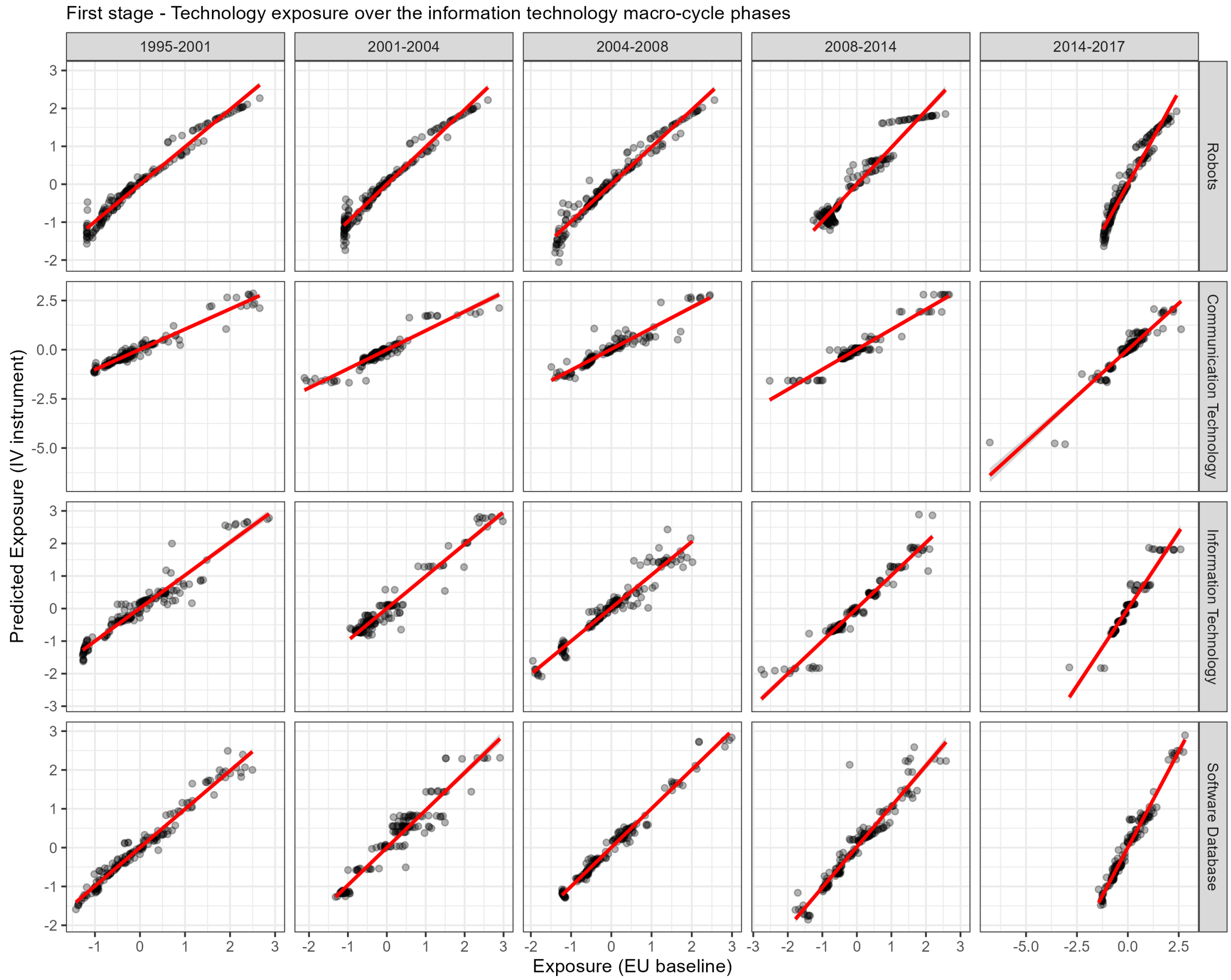
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by robot investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with 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)

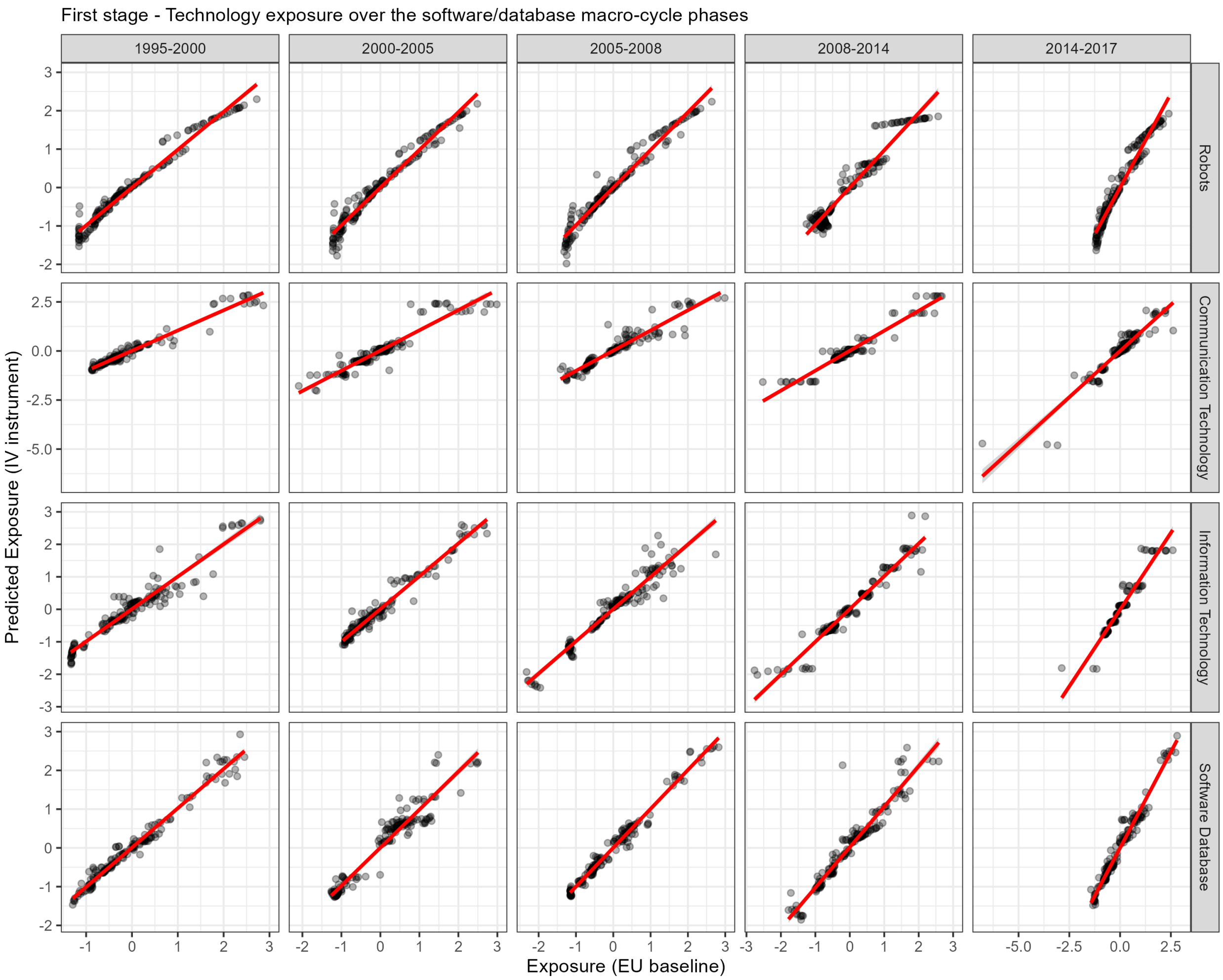


Notes: This figure presents the first-stage regressions for the technology exposure in European regions by IT investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed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

D.1 Technology stock

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.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.

E Technological Cycles: Summarizing Major Developments

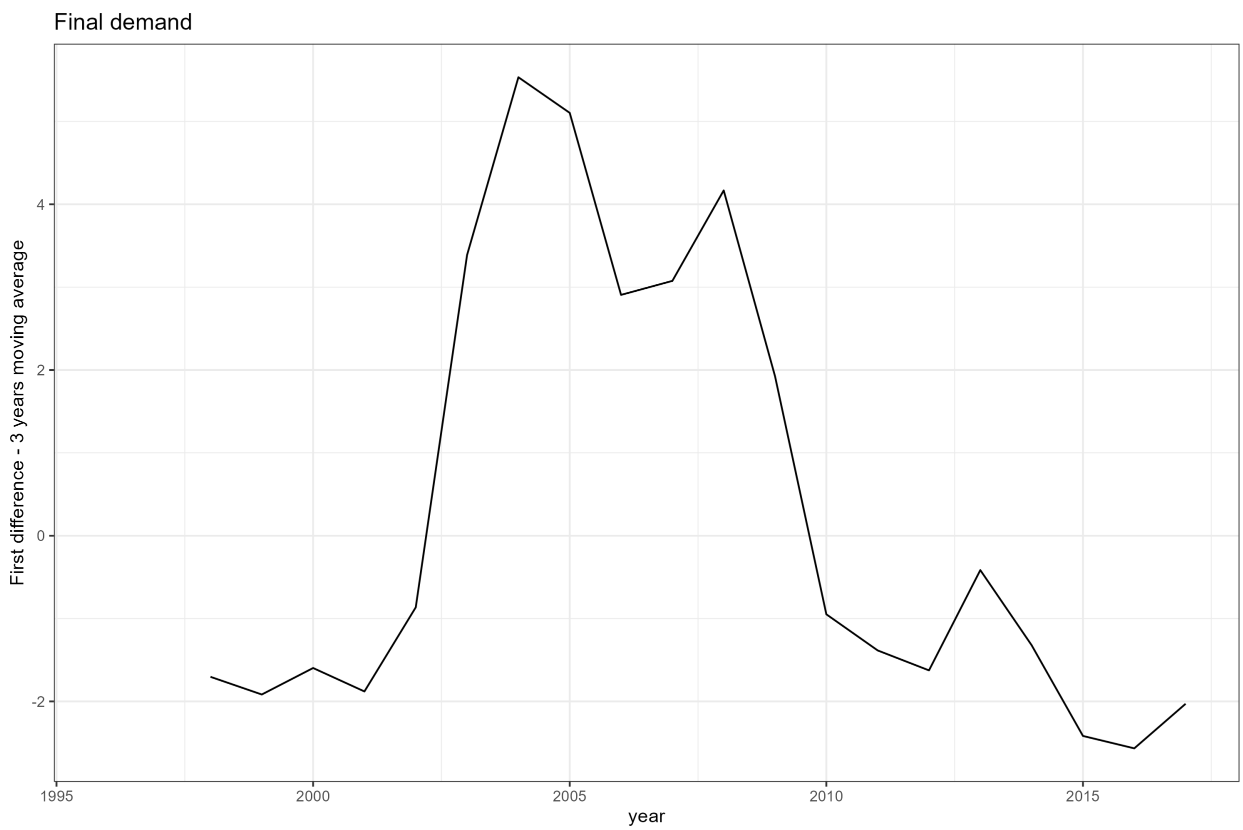
E.1 Cycle 1.: Web 1.0 (1990–)

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

Advancements in mainframes and microcomputers trace back to 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).[26] Concurrently, the development of newer and more user-

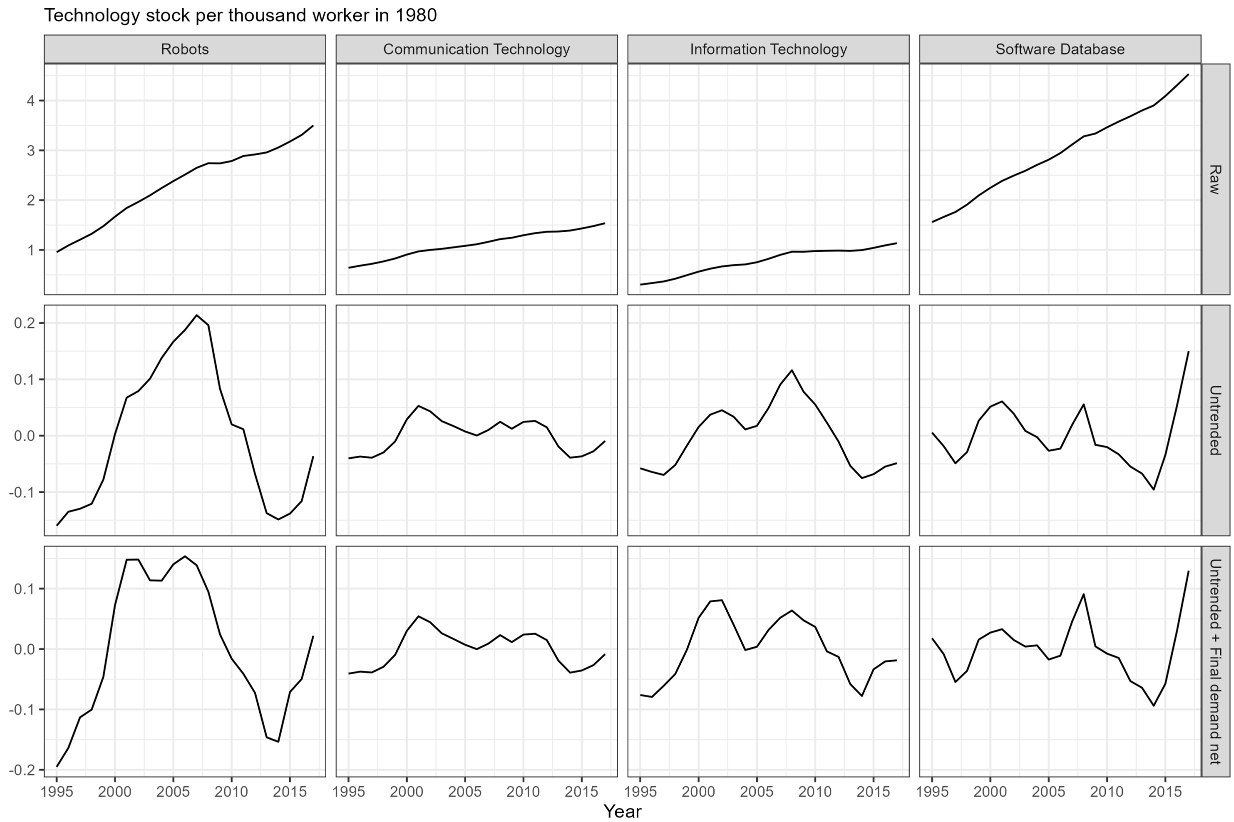
[26] In the US, private fixed investment in IT grew by around 98% between 1970 and 1999 (Mowery and Simcoe 2002).

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 worker at the EU level, representing the aggregate data for the 12 European countries in the sample. The series has been smoothed by taking the 3-year moving average.

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. 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).

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)

friendly operating systems, such as Windows 3.0 in 1990, the open-source operating system Linux in 1991, and Windows 1995, further facilitated this 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), the development of the HTTP protocol and the HTML language, and the introduction of 'browsers'—platforms designed for reading HTML documents (Mowery and Simcoe 2002). HTML and HTTP, 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 World Wide Web (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, simplifying and standardizing the visualization of documents online.

By 2002, over 50% of firms with 10 or more employees were utilizing the internet (Pilat 2005).[27] The dramatic diffusion of the internet changed the dynamics of retail, giving 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 communication and information technology has brought about significant changes in the organizational structures of firms, impacting business organization, communication with customers and suppliers, and work practices. These technologies typically replaced certain activities, particularly those that are easier to codify and program, while also creating new ones. Qualitative research conducted at the firm level has illustrated these changes. Autor et al. (2002) provide an interesting example with a case study on the adoption of check imaging and OCR software in a U.S. bank. On one hand, the technology facilitated the automation of check reading, making the check electronically available for all workers. This led to the reorganization of certain activities by managers, resulting in a more specialized structure of workers. Specifically, before the introduction of digitalization, an activity like check exception examination involved around 650 clerks in 1994. As checks needed to be physically present for examination, one worker oversaw the entire process per check. After the adoption of informatization, which allowed checks to be electronically accessible and utilized by multiple workers simultaneously, this job was broken down into more specialized tasks: processing overdrafts, implementing stop payment orders, and signature verification (Autor et al. 2002).

E.2 Cycle 2.: Graphical User Interface & Web 2.0 (2005–)

Gradually, developments in the internet led to a newer phase known as 'Web 2.0.' There is no precise definition of the term; instead, it is described by the dimensions it encompasses. These dimensions include technological aspects such as AJAX, RIA's, and XML/DHTML,

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

Table E.2: Technologies that characterized cycle 2. 2005–

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)

principles like participation, collective intelligence, and a rich user experience, as well as applications and tools such as Wikipedia, Flickr, and Mashups (Kim et al. 2009). The key characteristic of this phase is the perception of the internet as a collaborative platform where users can actively contribute to the development and improvement of applications. During this period, social media platforms developed their own APIs, becoming the primary connection channel between individuals (Lane 2019). This facilitated the creation of new applications and services that seamlessly integrated with social media platforms.[28]

Another notable feature of this phase is the increasing data intensity of applications, with their improvement closely tied to reaching a broader user base (O'Reilly 2007). The abundant data flowing through social media platforms has become a cornerstone for companies, allowing them to tailor their advertising based on consumers' preferences. Consequently, data analytics has shifted from relying on structured data to unstructured data, where natural processing methods have gained prominence (Lee 2017). In the mid-2000s, cloud computing gained widespread use among businesses. In 2006, Amazon introduced its Elastic Compute Cloud Commercial Services. Private clouds were already available by 2008, although they were not very popular. In 2010, Microsoft and other companies also launched their cloud computing services, making them more accessible, user-friendly, and affordable (Foote 2021).

According to Eurostat, by 2021 around 40% of the EU enterprises use cloud computing services, though the percentage varies substantially across countries.[29]

As firms increasingly invest in cloud computing (CC) services, the evidence suggests a negative association with IT capital and software investment. Firms' fixed capital in IT tends to decrease, while these services enable the growth of start-up firms as well as small and medium enterprises (SMEs) (Bloom and Pierri 2018, DeStefano et al. 2023). This outcome appears to be driven by the cost reduction that cloud services offer in comparison to the high fixed costs associated with ICT investment, which create substantial entry barriers for new firms (Etro 2009). In terms of employment consequences, the creation of SMEs

[28]In 2007, Apple initiated the 'App Revolution' by launching the software development kit for third parties. Developers could now create apps accessible on any iPhone. The App Store was launched in 2008, followed by the introduction of Google Play in 2012 (Crook 2018).

[29]In Sweden, Finland, Netherlands and Denmark more than 60% of the enterprises use cloud computing services. For detailed figures, please refer to EUROSTAT website.

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)

facilitated by CC services is particularly noteworthy. Given that SMEs are associated with high employment growth, the emergence of these types of firms enabled by CC services translates into positive employment outcomes (Etro 2009, Bloom and Pierri 2018).

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

During this period, Internet of Things (IoT) became widespread, often described as a set of technologies enabling physical objects—equipped with installed sensors—to communicate and share data with computing systems through wired or wireless networks, without the need for human mediation (Lee 2017).[30] In conjunction with social media websites, IoT is poised to become another significant source of data generation, encompassing images, videos, and audio (Lee 2017). This technology is pervasive across various sectors, being used in aerospace and defense, agroindustry (precision agriculture, where sensors monitor conditions like water levels, plant and soil health), automotive, pharmaceuticals, consumer goods, chemical industry, and information and communication technologies (ICTs) (Andreoni et al. 2021).[31]

Derived from the widespread internet penetration in the previous period, the influence of big data and data analytics experienced a significant surge. For instance, Gupta and Rani (2019) demonstrates that research publications associated with big data in 2017 were 126 times higher than in 2011. This coincided with the creation of several big data processing platforms, many of which became widely available in 2013 through incorporation into Apache Gupta and Rani 2019.[32] According to Gupta and Rani (2019), Apache Spark is one of the most popular systems for large-scale data processing, outperforming Hadoop by working faster and utilizing in-memory processing rather than a file system (IBMCloudEducation 2021). Other platforms capable of real-time analytics and processing were released during

[30] 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).

[31] For a comprehensive review of the use of IoT in different sectors, refer to Andreoni et al. (2021).

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

these years, such as Apache Storm and Apache Samza—used for data monetization, cybersecurity and threat detection, and performance monitoring, among other applications (Gupta and Rani 2019).[33] Overall, the compound annual growth rate for social media analytics is projected to be 27.6% between 2015 and 2020 (Lee 2017).

Another technology that has garnered increasing attention is artificial intelligence (AI). Although AI lacks a unique definition, it is generally described as a subset of computer science designed to train machines to perform cognitive activities associated with human intelligence, such as learning, problem-solving, and interaction (Brynjolfsson and McAfee 2014, Baruffaldi et al. 2020). The two major components of AI are machine learning and deep learning, both relying on the development of neural network techniques.

Given its ability to perform various functions, AI has found widespread applications across several industries (Cockburn et al. 2018). Among the activities it can undertake, we can list 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 pre-existing 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,[34] and a pivotal development in 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

[33] An interesting feature highlighting the strong connection of these phases with Web 2.0 is that these platforms have been developed by social media companies. BackType developed Apache Storm, and LinkedIn developed Apache Samza.

[34] 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.

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).