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

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July 2026

Abstract

This paper examines how the labor market effects of automation and digital technologies vary across their technology life cycles. Using data for 158 European regions from 1995 to 2017, we study the phase-specific impacts of robots, information and communication technologies (ICT), and software and databases (SDB) on employment and wages. We identify distinct technology life cycles and their early and mature adoption phases by applying a structural break methodology to investment dynamics. To address endogeneity in regional exposure, we employ a shift–share instrumental-variable strategy that leverages US investment patterns interacted with pre-determined regional industrial structures. We find that labor market effects differ systematically across both technologies and life-cycle phases. Early adoption is skill-biased for intangible digital technologies: exposure to SDB during early diffusion is associated with declining employment and rising wages. In contrast, early ICT adoption is characterized by employment expansion concentrated among lower-paid workers, consistent with productivity-driven demand growth, while robots exhibit largely skill-neutral effects in early diffusion. For tangible technologies, displacement effects emerge in mature adoption phases. Across technologies, labor market adjustment operates mainly through the services sector, even when adoption occurs in manufacturing (robots). Our findings demonstrate that aggregate estimates of ICT and robots often mask opposing life cycle phase- and technology-specific dynamics.

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

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1 Introduction

The tasks performed by workers and the skills required to operate new digital and automation technologies evolve both across technological breakthroughs and over the technology life cycle itself (Langlois 2003; Vona and Consoli 2015; Cirillo et al. 2023; Kogan et al. 2023; Ciarli et al. 2021; Prytkova et al. 2025). A central insight of this literature is that technological change is not a one-time shock, but a dynamic process in which adoption, learning, and standardization unfold over time, reshaping labor demand in phase-specific ways. Yet, empirical assessments of automation often abstract from these dynamics, estimating average effects that conflate distinct stages of diffusion.

A technology life cycle typically spans several stages—from research and development, to market introduction, growth, maturity, and eventual decline—each characterized by distinct rates of innovation, diffusion, and investment (Tushman and Anderson 1986). Consistent with this view, technology adoption follows a well-documented logistic pattern (Geroski 2000). Adoption initially accelerates rapidly following major breakthroughs, driven by early and majority adopters (Rogers 1962). As diffusion approaches saturation, investment growth slows and shifts toward more standardized technology vintages, marking the transition to maturity. These transitions are often visible as structural changes in investment dynamics, reflecting shifts in both technological opportunities and economic use.

Theories of technology and labor markets predict that employment and skill effects vary systematically across these phases. During early adoption, new technologies are expected to be skill-biased, as implementation relies on tacit knowledge, experimentation, and complementary organizational change that require highly educated workers (Tushman and Anderson 1986; Bartel and Lichtenberg 1987; Aghion 2002; Sanders 2013).[1] As learning progresses and technologies become more standardized, firms are better able to integrate them into production, potentially expanding output and employment through productivity gains—or, alternatively, substituting technology for labor as tasks become codified (Vona and Consoli 2015).[2]

Despite the relevance of this framework for understanding the labor market impact of technologies, most empirical evidence focuses either on single technologies or on average

[1] Bartel and Lichtenberg (1987) argues that education is a prerequisite for adopting new technologies, implying that firms initially increase demand for skilled workers. Aghion (2002) links within-group wage inequality to the diffusion of new machine vintages, emphasizing that only a subset of workers can adapt to emerging technologies.

[2] Galor and Tsiddon (1997) distinguish between the invention and diffusion phases of a technological paradigm. When a novel technology emerges, ability and adaptability become more important; as the technology matures and becomes easier to use, this selection effect weakens. Extending the routine-biased technical change framework, Vona and Consoli (2015) propose a technology life-cycle theory in which early adoption depends on highly skilled experts, while displacement of routine and lower-skill workers emerges later, once technologies become standardized and widely deployable.

effects over long periods, abstracting from the phase-specific dynamics implied by theory—particularly for recent waves of digitalization and automation. Moreover, the extent to which these predictions generalize across different types of technologies—tangible versus intangible, hardware versus software—remains an open question.

This paper addresses this gap by examining how regional employment and wages respond to exposure to robots, information and communication technologies (ICT), and software and databases (SDB) over distinct phases of their technology life cycles. By explicitly linking investment dynamics to labor market outcomes, we provide new evidence on when—and for which technologies—skill bias, displacement, or demand expansion dominates, offering a more nuanced assessment of the technology life-cycle theory of employment impacts.

We begin by identifying distinct technology life cycles based on investment dynamics. Using a multiple structural break methodology (Bai and Perron 2003) applied to time series of technology investment per worker, we identify periods of rapid expansion and subsequent maturation for each technology. Because comprehensive firm-level adoption data are unavailable at the regional level, changes in aggregate investment serve as a proxy for shifts in adoption intensity. We validate the resulting breakpoints against well-documented technological developments, allowing us to distinguish successive digital eras (cycles)—Web 1.0, the diffusion of graphical user interfaces and cloud computing, and the rise of big data and artificial intelligence—as well as two major phases in the evolution of robotics, corresponding to pre- and post-AI-enabled systems. Our analysis further decomposes these cycles into phases of acceleration (early adoption) and deceleration (maturity).

We then estimate the effects of technology exposure on regional labor market outcomes across these life-cycle phases. Specifically, we examine how exposure to each technology affects the employment-to-population ratio and average wages. Changes in employment reveal whether technology adoption is associated with labor displacement, labor reinstatement, or employment-neutral adjustment, while wage responses provide indirect evidence on skill bias. In the absence of consistent regional occupational data by skill over this period, we follow the literature in interpreting the joint behavior of employment and wages as informative about the composition of labor demand (e.g., Diamond 2016; Shapiro 2006).

To address endogeneity concerns in regional technology adoption, we employ a shift–share instrumental-variable strategy that leverages supply-side exogenous variation in technology investment in the United States. Specifically, we instrument regional exposure in Europe with US investment in the same technologies and life-cycle phases, interacted with regions' pre-determined industrial employment structure. This approach builds on and extends existing work on technology and labor markets (Chiacchio et al. 2018; Aghion et al. 2019; Acemoglu and Restrepo 2020; Dauth et al. 2021; Jestl 2024) by explicitly incorporating technology life-cycle dynamics into the identification strategy.

Our empirical analysis covers 158 NUTS-2 regions across 12 European countries. We combine data from EU-KLEMS for ICT and SDB investments, the International Federation of Robotics (IFR) for robot adoption, and ARDECO for regional labor market outcomes. This integrated framework allows us to trace how the employment and wage effects of automation and digital technologies evolve over time, shedding new light on the phase-specific nature of technological change.

Our results show that the labor market effects of digital and automation technologies vary systematically over the technology life cycle, and that these dynamics differ sharply across types of technologies and their vintages.

First, consistent with technology life-cycle theories, we find that employment and wage effects differ markedly between early adoption and maturity phases. However, evidence for early-phase skill bias is confined to intangible digital technologies. In contrast, for tangible digital technologies such as ICT hardware, early adoption is associated with net employment gains concentrated among lower-paid workers. This pattern aligns more closely with theories emphasizing productivity-driven demand expansion, task creation, and complementary service growth during the initial integration of ICT (Mazzolari and Ragusa 2013; Pantea et al. 2017). For robots, we find no significant changes in either employment levels or skill composition during early adoption phases in the industry in which they are adopted, suggesting that adjustment frictions and learning delays may dampen short-run labor market responses (Domini et al. 2021).

In the maturity phase, the evidence is more consistent with canonical predictions of labor displacement. For ICT, we observe employment declines as technologies become more standardized and tasks more easily routinized. Wage effects in these phases are weak or imprecisely estimated, preventing us from conclusively identifying whether displacement is concentrated among the least skilled, but the employment patterns suggest rising substitution between labor and technology as adoption matures.

Beyond life-cycle phase dynamics, our analysis yields three additional insights. First, we show that labor market impacts differ not only across technologies but also across technological breakthroughs (cycles) within the same broad category. Most of the employment and wage effects observed between 1995 and 2017 are driven by the first major digital and automation waves—Web 1.0 for ICT and the initial diffusion of industrial robots—while later breakthroughs exhibit more muted effects.

Second, ICT and SDB often exert opposing effects on regional labor markets. Except during the most recent wave of Big Data and AI, ICT adoption tends to reinstate lower-paid jobs, while SDB adoption is associated with labor displacement and rising wages. In regions where adoption of ICT and SDB progresses in tandem, these effects largely offset each other, resulting in minimal net employment changes. Where ICT adoption dominates, early diffusion is associated with productivity-driven labor demand expansion; where SDB adoption dominates, adjustment follows the skill-biased pattern predicted by life-cycle theories.

Third, we document substantial sectoral reallocation and spillovers. Although industrial robots are primarily adopted in manufacturing, their positive regional employment effects materialize almost entirely in services within the same region. ICT and SDB—adopted in both manufacturing and services—also exert their strongest employment and wage effects in services. This suggests that regional labor market adjustments appear to be driven less by direct technological substitution within adopting industries than by changes in local demand for complementary services.

Finally, we subject our findings to a comprehensive set of validity and robustness checks. We address concerns about pre-existing trends by controlling for pre-period employment and wage dynamics; we assess the identifying variation in our Bartik IV strategy using Rotemberg weights and show that results are not driven by a small set of influential country–industry shocks; and we demonstrate robustness to alternative definitions of technology life-cycle phases. Across all exercises, the main results remain intact, reinforcing the interpretation that our results reflect technology-driven labor market adjustments over the technology life cycle rather than artifacts of identification or periodization choices.

This paper contributes to the large and growing literature on the labor market effects of digitalization and automation (e.g., Goos et al. 2014; Chiacchio et al. 2018; Graetz and Michaels 2018; Aghion et al. 2019; Acemoglu and Restrepo 2020; Cirillo et al. 2021; Gregory et al. 2022). Existing studies document heterogeneous effects of robots and digital technologies across countries, industries, and periods. For example, while U.S. evidence points to negative employment effects of robots (Acemoglu and Restrepo 2020), results for Europe are mixed, ranging from negative (Acemoglu et al. 2020) to null (Dauth et al. 2021) and positive effects (Reljic et al. 2023, Mann and Püttmann 2023). More recent work highlights that impacts differ across technologies such as robots, ICT, and software (Blanas 2023; Jestl 2024; Segarra-Blasco et al. 2025) and across time, depending on whether substitution or compensation mechanisms dominate (Antón et al. 2022).

Our paper advances this literature along two main dimensions. First, we bring a technology life-cycle perspective to the empirical analysis of labor market effects, focusing explicitly on the adoption phase rather than on the product or invention cycle. While prior work emphasizes that high-skill workers are disproportionately involved in the development of new technologies, far less is known about how labor demand adjusts as technologies diffuse and mature. This distinction is crucial: adoption can generate very different distributional outcomes depending on whether productivity gains, labor hoarding, and demand expansion dominate, or whether task codification and substitution prevail (Autor et al. 1998; Autor et al. 2003; Acemoglu and Autor 2011; Acemoglu and Restrepo 2019). By explicitly identifying early and mature adoption phases for robots, ICT, and SDB, we test a core prediction of technology life-cycle theories—that skill bias is strongest during early adoption and displacement emerges as technologies become standardized (Tushman and Anderson 1986; Bartel and Lichtenberg 1987; Aghion 2002; Vona and Consoli 2015). Our results reveal substantial heterogeneity across technologies. Intangible technologies such as software and databases conform closely to the canonical skill-biased life-cycle pattern. In contrast, tangible technologies such as ICT hardware and robots exhibit weaker early skill bias, with employment effects shaped by productivity-driven demand expansion, labor hoarding, and organizational adjustment frictions (Domini et al. 2021). For robots, labor market effects operate primarily through regional spillovers into ancillary sectors rather than direct displacement in adopting industries. These findings refine life-cycle theories by showing that phase-specific labor market effects depend critically on technological characteristics.

Second, we clarify the relationship between short-run and long-run employment effects of automation and digital technologies. A well-established literature argues that, in the long run, productivity gains, demand growth, and the creation of new tasks offset displacement effects, leaving aggregate employment largely unchanged despite substantial reallocation (Simon 1960; Vivarelli 1995; Autor and Salomons 2018; Aghion et al. 2022; Autor et al. 2024). However, much empirical work evaluates technology impacts over broad and often arbitrary time windows that span multiple technological breakthroughs and adoption phases.

Our approach instead anchors the analysis to the specific life cycles of robots, ICT, and SDB. This reveals that modest or insignificant long-run effects can mask sizable short-run adjustments in employment levels and composition that are highly relevant for workers and policymakers. Moreover, we show that estimated effects are sensitive to the timing of the analysis: pooling across different technologies or life-cycle phases can yield misleading or inconsistent conclusions. By aligning empirical windows with technology-specific adoption dynamics, we provide a more precise account of how and when labor markets adjust to technological change.

The remainder of the paper is organized as follows. Section 2 describes the data sources and variables used in the analysis. Section 3 identifies the technology life-cycle phases and the associated major innovation breakthroughs for robots, ICT, and software and databases. Section 4 outlines the empirical framework and the instrumental-variable strategy tailored to the technology life-cycle setting. Section 5 presents the main results on the employment and wage effects of automation and digital technologies across life-cycle phases and relates them to the theoretical predictions. Section 6 reports a comprehensive set of validity and robustness checks. Section 7 concludes.

2 Data

2.1 Sample

We analyze the impact of technology exposure on labor market outcomes across 158 NUTS-2 regions in 12 European countries over the period 1995 to 2017. The 12 countries included are Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, the Netherlands, Spain, and Sweden.[3]

2.2 Data Sources and Variables

Labor Market. We examine labor market outcomes at the regional level, focusing on variables related to employment and wages, constructed using NUTS-2 level data from the ARDECO database (2022 release).[4]

We use the employment-to-population ratio as our main employment outcome, defined as the share of employed individuals aged 15 to 64 relative to the total population in the same age group.[5]

For wages, we use the average annual wage compensation per worker, expressed in thousands of euros (2015 values), computed by dividing total employee compensation by the level of total employment. While this measure does not capture within-region wage inequality, it is a proxy for the net skill-bias of labor demand: rising average wages (controlling for employ-

[3]We focus on this subset of European countries to ensure the consistency of our instrumental variable strategy. First, the shift-share instrument we adopt in the paper requires sectoral employment shares from 1980, which are unavailable for several Eastern European countries. Second, identifying technology investment life cycles requires a balanced panel of technology stocks for the period 1995–2017; however, ICT and software and database data are not available in EUKLEMS for most Eastern European countries before 2000. An unbalanced panel would bias the identification of technology life cycles towards the subset of countries with data available since 1995.

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

[5]We acknowledge that the ratio suffers from the limitation that the denominator may grow more than the numerator in regions with an aging population. However, in the ARDECO database, we only have information for the total population, so it is not possible to exclude people with 65 or older. If regions that are aging faster also have an incentive to adopt digital technologies, we expect to see a negative relation between technology adoption and the employment-to-population ratio.

ment levels) generally imply a shift in composition toward higher-paid, higher-skill tasks (Diamond 2016; Shapiro 2006).

Automation Technologies. We consider three automation technologies, differentiating between tangible and intangible investment in digital automation:

1. Robot: "programmed actuated mechanism with a degree of autonomy to perform locomotion, manipulation or positioning" (ISO 8373:2021);

2a. Communication Technology (CT): "specific tools, systems, computer programs, etc., used to transfer information among project stakeholders" (ISO 24765:2017);

2b. Information Technology (IT): "resources required to acquire, process, store and disseminate information" (ISO 24765:2017);

3a. Computer Software: "computer programs, procedures and possibly associated documentation and data pertaining to the operation of a computer system" (ISO 24765:2017);

3b. Database: "collection of interrelated data stored together in one or more computerized files" (ISO 24765:2017).

We aggregate IT and CT into a single category of tangible digital capital, and computer software (3a) and databases (3b) into a single category of intangible capital, labeled software and databases (SDB).[6]

Control Variables. To account for other factors that might influence regional labor market outcomes, we include two control variables (both in shift-share) to isolate the role of investment in automation. First, we adjust for changes in final domestic demand using the real consumption index from the Inter-Country Input-Output database.[7] We do this to absorb the effect associated with business cycles in our outcome variables. Second, we consider the potential impact of trade and international competition by controlling for imports from China recorded in the OECD Trade in Value Added database.[8] This control captures the adverse effects of international competition on local labor markets (Autor et al. 2013, Dauth et al. 2014, Autor et al. 2015).

Instrumental Variable. To address the endogeneity in the relationship between the decision to invest in automation technologies and labor market outcomes, we use data on investment in the United States in similar automation technologies as an instrument for investment

[6]The EU-KLEMS data we use (discussed further below) do not clearly distinguish between software and databases. This is because it retrieves data from the national statistical offices, which follow the System of National Accounts (SNA) 2008, in which software and databases are treated as a single category.

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

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

by European regions. These data are from the IFR (for robots) and EU-KLEMS (for ICT and SDB).To construct our instrument (described in Section 4), we normalize the technology stock using sectoral employment data from 1980, sourced from the OECD Annual Labor Force Statistics (ALFS).[9]

3 Technological Breakthroughs and their Life Cycles

Technological progress occurs in clustered waves of breakthrough inventions and their diffusion. Major breakthroughs trigger cascades of incremental improvements, sustaining adoption until the technology matures and further innovation stagnates (Silverberg and Verspagen 2003).

In this section, we adopt a data-driven approach to identify these technology life cycles in digital and robot technologies. Using investment data, we characterize the temporal diffusion of digital technologies and industrial robots across Europe and identify cyclical patterns in investment intensity that correspond to distinct stages of the technology life cycle. We interpret periods of accelerating investment as early diffusion phases following a breakthrough innovation characterized by experimentation and the accumulation of related tangible or intangible capital. We instead interpret periods of decelerating investment as transitions toward maturity, marked by standardization and saturation, where innovation is limited to incremental upgrading. Consistent with the logistic model of technological diffusion (Geroski 2000), these phases capture the temporal evolution of technological adoption in European economies.

Having identified these diffusion cycles directly from the data, we then confront them with qualitative evidence from the innovation and engineering literature. In particular, we examine whether the estimated turning points coincide with historically documented technological breakthroughs in digital technologies (ICT and SDB) and industrial robotics since the mid-1990s. This comparison allows us to interpret each empirically identified cycle as a distinct wave of technological innovation and related diffusion.

3.1 Technology Life Cycles in Digital and Robot Technologies: A Data-Driven Approach

Using investment data for robots and digital technologies, we test whether their diffusion over time follows a cyclical behavior. Specifically, we construct aggregate investment stocks for each technology across European countries, expressed per thousand workers (base year 1980,

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

constant prices). As shown in Figure A.1 in the appendix, investment in both digital technologies and robots has increased annually since 1995.

To identify changes in technology-investment dynamics, we apply the multiple structural-break procedure of Bai and Perron (2003) to the time series of technology stocks per thousand workers, estimating separate models for robots and digital technologies. Intuitively, the method approximates each investment trajectory with a sequence of linear segments and identifies dates at which allowing the regression parameters to change substantially improves the model's fit. It jointly determines the number and timing of these breakpoints, thereby partitioning the investment trajectory into statistically distinct regimes.[10]

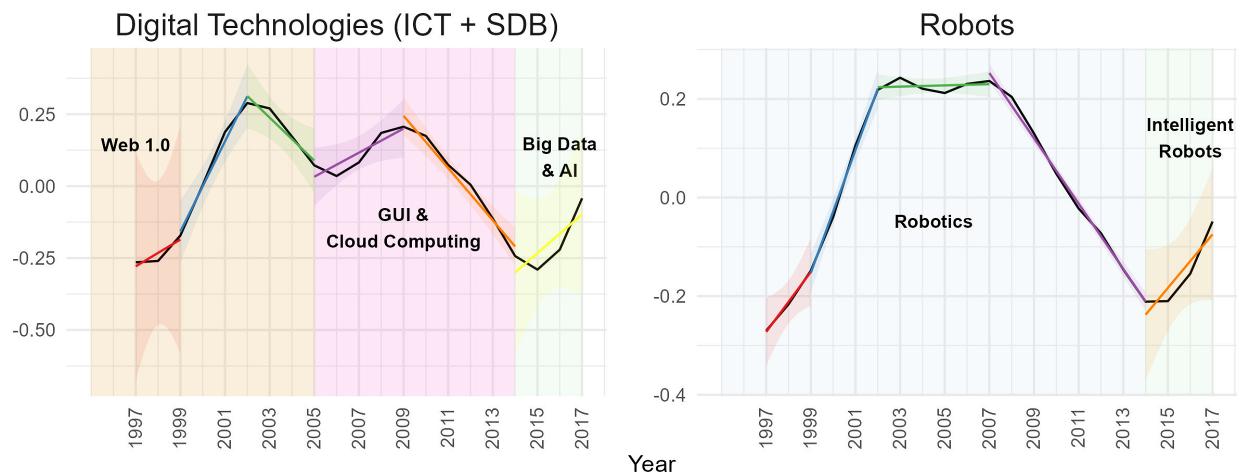
Before implementing the Bai–Perron structural break analysis, we preprocess the investment time series to isolate technology-specific cycles from broader macroeconomic fluctuations (business cycles). Specifically, we regress technology stock per worker on a real consumption index and a deterministic time trend, and use the residuals from this regression as a detrended investment series. This procedure removes the influence of aggregate demand and secular trends, ensuring that the detected breaks reflect shifts in technological investment rather than cyclical variations in output or consumption.

For each technology, we then estimate a linear model and apply the Bai–Perron algorithm to identify statistically distinct regimes in the investment trajectory. Each regime corresponds to a segment with a different slope, capturing acceleration or deceleration in investment intensity. Figure 1 illustrates the resulting investment cycles. We interpret positive and statistically significant slopes as expansion phases, i.e., the early phase of diffusion driven by early and majority adopters experimenting with the initial vintages of the technology; negative slopes as contraction phases, i.e., the maturity phase when late adopters integrate standardized vintages of these technologies; and statistically flat segments as plateaus, i.e. transitions between the early and the mature phase. This data-driven segmentation yields a set of breakpoints that map closely onto the technology breakthrough identified from the history of these technologies (as detailed below). The sequence of the estimated slopes confirm the cyclical behavior predicted by the diffusion literature: each breakthrough is followed by an expansion in investment, followed by a contraction leading to the next breakthrough.

We examine the estimated cycles in more detail. For *digital technologies*, the data reveal two life cycles and the beginning of a third one over our sample period. Investment accelerates from the start, in 1995, until around 2002, followed by a phase of decelerating growth lasting

[10] For a given number of breaks, the algorithm searches over all admissible combinations of break dates, subject to the requirement that each regime contains at least three observations. It selects the partition that minimizes the total sum of squared residuals across the resulting segments. We then choose the number of breaks associated with the lowest Bayesian Information Criterion (BIC), considering up to five breaks. Thus, neither the number nor the dates of the breaks are imposed in advance.

Figure 1: Investment Cycles Between 1995 and 2017



Notes: This figure illustrates the investment cycles in robots and digital technologies. We first extract cyclical components by regressing the three-year moving average of each technology stock on a linear time trend, controlling for real consumption to account for business cycle fluctuations. We then apply a simultaneous multiple-breakpoint estimation procedure, following Bai and Perron (2003), to each technology series in order to partition it into m distinct cycles (i.e., segments).

until approximately 2005. This pattern is consistent with the transition from an early diffusion phase to a more mature stage of adoption.

A second cycle begins in the mid-2000s. Between 2005 and 2009, investment growth accelerates again, indicating the diffusion of a new technological wave. After reaching a peak around 2009, investment enters a decelerating phase that extends until roughly 2014, signaling another transition toward maturity. From 2014 onward, we observe a renewed acceleration in investment, marking the onset of a third diffusion phase that remains ongoing through 2017, the final year of available data.

In the case of *robots*, the data indicate two distinct diffusion cycles. Investment accelerates from 1995 until approximately 2002, reflecting an initial phase of rapid adoption. This is followed by a plateau and subsequent maturity phase extending through the late 2000s. Beginning around 2014, investment growth accelerates once more, indicating the early diffusion of a new generation of robotic technologies. As with digital technologies, this latest phase is still unfolding at the end of the sample period.

As a robustness exercise, we apply the multiple structural breakpoint procedure directly to the first-differenced series of technology investments and compare the resulting dynamics with those obtained from the detrended, net-of-business-cycle investment series. The two alternatives yield broadly consistent subperiods. This convergence reinforces the reliability of the identified turning points in investment in digital technologies and robots, and supports their interpretation as distinct waves associated with major technological breakthroughs. The results obtained from this alternative specification are discussed in detail in the robustness checks in Section 6.

3.2 Breakthroughs in Automation Technologies

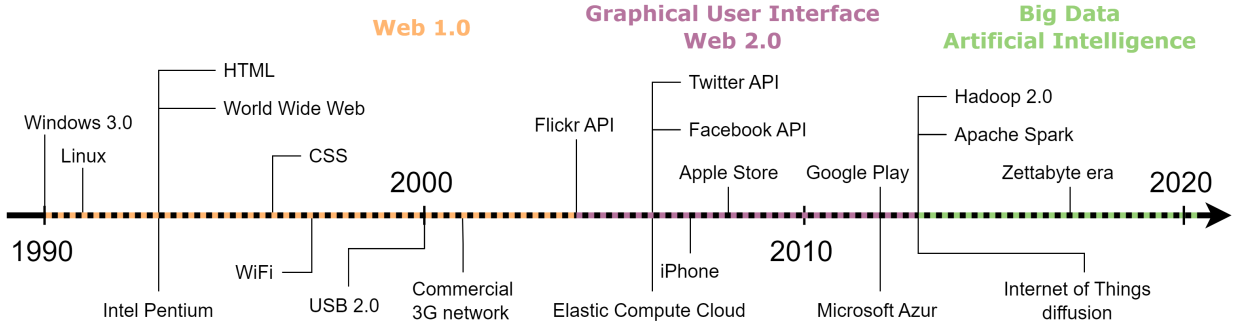
While the analysis in the previous section identifies diffusion cycles solely based on investment dynamics, the timing of these phases closely aligns with major technological breakthroughs documented in the innovation and engineering literature. The discussion that follows draws on this literature to describe the technological breakthroughs, thereby providing an external consistency check for the identified cycles and a technological interpretation of our empirical results.

3.2.1 Digital Technologies

The information and communication technology (ICT) revolution, originating in the early 1970s, constituted a system-wide transformation driven by mutually reinforcing technological advances (Freeman and Perez 1988; Perez 2010). According to Nuvolari (2020), the ICT complex rests on four foundational and interdependent components: electronic hardware, computational power (semiconductors and computers), software, and networking infrastructure. Radical progress in any of these domains has historically triggered complementary innovations in the others. Among these, the invention and continual refinement of the microprocessor represented the pivotal breakthrough—dramatically expanding computational capacity while sharply reducing costs and enabling widespread diffusion of digital devices (Freeman and Louçã 2001).

Figure 2 summarizes the major innovation waves in digital technologies since the early 1990s, distinguishing three radical transitions across ICT components. The first corresponds to the emergence of Web 1.0 (1993–2004), which marked the commercial expansion of the internet and the standardization of digital communication protocols. The second encompasses the diffusion of Graphical User Interfaces (GUIs) and the rise of Cloud Computing (2004–2013), which redefined user interaction and enabled scalable data storage and processing. The third breakthrough—Big Data and AI (2013–present)—integrates advances in data analytics, machine learning, and computational infrastructure. These three breakthroughs coincide with the ones identified above (see Figure 1). We outline the defining characteristics of each phase below, with detailed technological documentation provided in Appendix E.

Figure 2: Main Digital Technology Innovations Since 1990



Notes: This figure presents the main digital technology innovations since 1990. The three digital technological cycles are Web 1.0 (1993–2004), Graphical User Interface and Web 2.0 (2004–2013), and Big Data and Artificial Intelligence (from 2013).

Web 1.0. The 1990s marked the mass diffusion of personal computing, driven by sharp declines in the size and cost of microprocessors and corresponding gains in processing capacity. The introduction of user-oriented operating systems—most notably Windows 3.0 and Linux—expanded the accessibility of information technologies (IT) to households and firms. Concurrently, the launch of the World Wide Web (WWW) in 1993 transformed communication technologies (CT) by enabling internet-based information exchange and commercial applications such as e-commerce. Software developments underpinned this early diffusion of ICT to end-users, though database-related investments remained limited, reflecting the nascent stage of digital data generation and storage.

Graphical User Interface and Cloud Computing. The second major digital breakthrough unfolded in the early 2000s with the advent of Web 2.0, underpinned by advances in Graphical User Interfaces (GUIs) and Cloud Computing. Building on the prior diffusion of the internet and mobile communication infrastructure, these developments enabled the widespread adoption of interactive, user-friendly devices such as smartphones. This period generated substantial network externalities (Mansell 2021) and supported the emergence of new digital services, including social media, e-commerce platforms, search engines, and data-driven applications. Concurrently, databases assumed a more central role in both production and consumption, facilitated by rising computational capacity and the standardization of Application Programming Interfaces (APIs), which allowed seamless integration and exchange of data across systems.

Big Data and Artificial Intelligence. The third digital breakthrough, beginning in the early 2010s, centers on the rapid expansion of AI, particularly through advances in machine learning and deep learning. This wave has been propelled by the convergence of three enabling factors: the exponential growth of data availability (Big Data), the surge in computational power made accessible through cloud infrastructures, and the refinement of neural network architectures. Simultaneous progress in networking and sensor technologies has also facilitated the emergence of the Internet of Things (IoT), which extends data generation and connectivity across physical devices.[11]

3.2.2 Breakthroughs in Robots

Robotics. The evolution of industrial robotics during the 1990s built upon the foundations of the third generation of robots (1978–1999) as classified by Gasparetto et al. 2019. This generation was defined by three core technological capabilities: (i) remote and self-programming functions enabled by embedded microprocessors; (ii) enhanced sensing and feedback systems that allowed limited adaptive responses to environmental conditions, such as visual and tactile inspection and servo control; and (iii) multi-axis movement, typically extending to six degrees of freedom (Savona et al. 2022).

Advances in communication protocols during this period—most notably the Internet, the World Wide Web, and emerging wireless standards—broadened the operational flexibility of robots, laying the groundwork for mobile robotic systems (Grau et al. 2017). These developments initially transformed automotive manufacturing, where automation was most concentrated, and subsequently began diffusing to other industrial sectors (Hägele et al. 2016; Gasparetto et al. 2019).

Despite steady technical improvements, no major discontinuity occurred until around 2010. The intervening years largely reflected incremental refinement of earlier designs. It was the convergence of robotics with digital and cyber-physical systems—collectively referred to as Industry 4.0 technologies—during the 2000s that ultimately set the stage for the next major breakthrough in robotic automation.

Intelligent Robots. The mid-2010s marked a decisive technological shift in robotics, driven by the integration of AI, advanced sensing systems, and the IoT. The combination of machine learning algorithms with high-resolution sensors and wireless communication technologies enabled robots to operate autonomously and coordinate dynamically with other connected devices. These advances expanded robotic mobility, facilitated multi-agent interaction (e.g., swarm coordination), and enhanced human–machine collaboration. The result was a new

[11] The IoT refers to technologies that enable sensor-equipped physical objects to communicate and exchange data with computing systems over wired or wireless networks without human intervention (Lee 2017). Together with social media platforms, IoT systems have become major sources of data fueling continued AI development.

generation of "intelligent robots" characterized by adaptive behavior, greater precision, and broader functional scope in industrial applications (Müller 2022).

4 Empirical Specification

We quantify the effects of exposure to robots, ICT, and computer software and databases (SDB) technologies on regional labor market outcomes in Europe across successive phases of their respective technology life cycles. We then estimate a baseline model that relates labor market adjustments to phase-specific technology exposure. To mitigate endogeneity concerns—particularly reverse causality and omitted demand shocks—we employ an instrumental variables (IV) strategy that instruments European technology investment with corresponding investment trends in the United States.

4.1 Shift-Share Technology Exposure in Technological Investment Phases

Since data on technology stocks for robots, ICT, and SDB are available only at the national level, we construct regional exposure measures using a standard shift–share framework (Chiacchio et al. 2018; Acemoglu and Restrepo 2020; Dauth et al. 2021; Jestl 2024). The exposure of region r to technology K over the period $[t, t+h]$ is defined as:

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

where $l_{ri,1980}$ is the share of employment in sector i in region r in the base year 1980, and $Tech_{c(r)i,t}^K$ is the national-level stock of technology $K \in \{ROB, ICT, SDB\}$ in sector i for the country $c(r)$ in year t per thousands workers in the same sector–country in 1980.

For robots, we use the number of robots (i.e., robot stock) in use in each sector at the country level from the 2019 Release of the IFR data (see Jurkat et al. (2022) for a comprehensive review of the data). Robots are present in three out of six sectors: Industry (B-E), Construction (F), and Non-Market Services (O-U).[12] Since approximately 30% of robots in IFR are not assigned to a sector, we proportionally reallocated them to sectors based on observed sectoral

[12]It is worth noting that IFR Release 2019 has information at ISIC Rev. 3.1. As the rest of our data sources are at ISIC Rev. 4 (which corresponds to NACE Rev. 2), we harmonized them to be compatible with the latter classification. Given that we only have access to 1-digit industry-level data in the ARDECO database, the conversion between Rev 2 and Rev 3.1 introduces marginal differences. Tables A.1 and A.2 provide more details on the harmonization.

robot shares.[13] Additionally, for countries where the number of robots is not available at the sectoral level for early years (such as the US), we estimate their number by distributing the total number of robots weighted by the average sectoral share using years with available data.[14]

To compute a measure of regional exposure to ICT and SDB, we use data from the EU-KLEMS database (Release 2021). Specifically, we use the capital stock (in 2015 volumes), derived from national accounts.[15,16] For Denmark and Sweden, we converted EU-KLEMS figures into euros using the nominal exchange rate from EUROSTAT.

By construction, the variation in exposure reflects changes in technology stocks, while holding regional sectoral employment shares fixed at their pre-period levels mitigates potential endogeneity from contemporaneous regional labor market adjustments.[17] Figure B.1 in Appendix B maps the regional distribution of this exposure measure for each technology over 1995–2017, highlighting the geographic concentration of technology exposure across European regions.

We adapt the shift–share framework to incorporate the segmentation of the 1995–2017 period into distinct sub-periods corresponding to the identified phases of each technology's life cycle. Let $t+h'$ denote a breakpoint—an intermediate year between 1995 and 2017—that separates two consecutive phases of the technology life cycle. We decompose the total exposure defined in Equation (1) into phase-specific components before and after the breakpoint:

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

By regrouping the terms and applying the same logic as in Equation (1), total exposure can be

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

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

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

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

[17]The exposure measure isolates the effect of technology accumulation, not shifts in regional sectoral composition. Using 1980 employment weights ensures exogeneity with respect to subsequent technology adoption. Appendix Section D.6 reports a robustness check using 1990 sectoral employment shares, showing that the main qualitative results are not driven by the initial-year choice.

expressed as the sum of the exposures estimated for each technological phase:

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

where $Exposure^K_{r,1}$ corresponds to the phase between 1995 and $t+h'$ and $Exposure^K_{r,2}$ captures the subsequent phase between $t+h'$ and 2017. This decomposition generalizes to any number of identified life-cycle phases:

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

where each $\tau \in \mathcal{T}$ denotes a distinct investment phase within the overall technology life cycle.

We apply an analogous decomposition to labor market outcomes, capturing regional adjustments across successive phases of technological investment. Formally,

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

where $y_{r,\tau}$ is the change in the labor market outcome of the region r during investment phase τ. Each $y_{r,\tau}$ thus isolates the within-phase adjustment in the relevant labor market indicator corresponding to the temporal segmentation of technology diffusion.

Throughout the remainder of the analysis, the unit of observation is defined at the level of the investment phase τ, distinguishing periods of acceleration and deceleration of investment identified in Section 3.1.

4.2 Baseline Specification

To estimate the relationship between regional labor market adjustments and exposure to technology K across the different phases $\tau \in \mathcal{T}$ of each technology's life cycle, we specify the following regression model:

$$y_{r,\tau} = \alpha + \beta\, Exposure^K_{r,\tau} + X'\gamma + \phi_{c(r)} + u_{r,\tau}, \qquad K \in \{ROB, ICT, SDB\}, \tag{3}$$

where $y_{r,\tau}$ is the *annualized* change in the labor market outcome for region r during phase τ;[18] $Exposure^K_{r,\tau}$ is the region's exposure to the focal technology $K \in \{ROB, ICT, SDB\}$ during phase τ;[19] and X' collects the control variables. These include the exposure to the other technologies $J \neq K$ measured over the same phase τ, which absorbs potential technological complementarity between robots, ICT, and software; the logarithm of the 1980 regional population; the change in final demand; trade exposure; and the change in the relevant outcome variable over the pre-period 1980–1994. This latter control captures persistent regional labor market dynamics, such as long-run secular decline in manufacturing regions, which may be correlated with historical sectoral composition and earlier phases of technology diffusion, but unrelated to recent technology adoption (Acemoglu and Restrepo 2020)—particularly for digital technologies whose adoption predates our main sample period. Incorporating pre-period outcome changes allows us to net out differential trends that could otherwise confound the estimated effects of technology exposure, thereby strengthening the exclusion restriction of the instrumental-variable strategy.[20] Finally, $\phi_{c(r)}$ are country fixed effects which absorb unobserved heterogeneity at the national level, and $u_{r,\tau}$ is the error term. All observations are weighted by the 1980 regional population. We cluster standard errors at the NUTS1 level (57 regions) to adjust for common group effects regions, avoiding the risk over-rejecting the null hypothesis.[21]

We standardize the exposure measures within each technological phase to enable direct comparison of effect magnitudes across technologies and life-cycle stages. With this normalization, the coefficients β represent the annualized change in the outcome variable y for a one-standard-deviation (1-SD) change in exposure to technology K during phase τ.

Changes in average wages are expressed as logarithmic differences. This allows the estimated coefficients to be interpreted as approximate percentage changes. Changes in the employment-to-population ratio are measured in levels, so the corresponding coefficients reflect percentage-point (pp.) variations.

4.3 Identification and IV Strategy

The relationship between automation investment and labor market outcomes is inherently endogenous. Three primary sources of endogeneity arise. First, investment decisions in au-

[18]Since the duration of life-cycle phases varies, annualization ensures that the magnitudes are comparable across phases.

[19]Because robots and the digital technologies follow different life-cycle periodizations (Section 3.1), Equation (3) is estimated separately for each focal technology over the phases of its own life cycle; ICT and SDB, which share a common periodization, are estimated over the same set of digital phases.

[20]As shown later in Section 6.3, this adjustment is especially relevant for ICT and software-related technologies, while leaving the main qualitative patterns unchanged.

[21]Clustering at the country level would yield only 12 clusters, too few for reliable cluster-robust inference.

tomation technologies respond to labor market conditions. Firms adopt robots, ICT, and software-data technologies partly in reaction to labor costs, labor scarcity, and institutional constraints (Bachmann et al. 2022; Presidente 2023). Consequently, regions with high wages or rigid labor markets may simultaneously experience both stronger automation investment and weaker employment growth, confounding causal inference.

Second, unobserved regional and sectoral characteristics—such as workforce skill composition, unionization, or historical specialization—jointly influence technology adoption and labor outcomes. These factors are often time-invariant or imperfectly measured, and while the inclusion of controls for real consumption (to proxy for cyclical demand), trade exposure, and country fixed effects mitigates part of this bias, it cannot fully remove it. For example, regions with a higher share of skilled labor may both adopt new technologies earlier and exhibit stronger employment performance through productivity and output expansion.

Third, measurement error poses an additional challenge. Robot data from the International Federation of Robotics (IFR) do not always allocate units precisely across sectors, while national accounting differences in the valuation of ICT tangible capital and software and data intangible capital introduce inconsistencies in EU-KLEMS data. These discrepancies likely attenuate OLS estimates toward zero, especially for intangible technologies.

Given these reverse causality, omitted-variable, and measurement-error concerns, the OLS coefficients from Equation (3) are likely biased. The sign and magnitude of the bias depend on the dominant channel of endogeneity for each technology.

To address these endogeneity concerns, we adopt an instrumental variable (IV) strategy that leverages global technology supply changes analogous to those of Acemoglu and Restrepo (2020), and consistent with recent applications to European regional labor markets (Antón et al. 2022; Jestl 2024). Specifically, we use US technological investment as an instrument for European technology adoption.

The identification relies on two key premises. First, relevance: US investment trends should predict European adoption patterns. This is plausible, given that global technological frontiers in robotics, ICT, and software–data systems are global, and are largely driven by innovation and capital accumulation in the US – with Europe being a follower rather than a leader in digital and automation technologies (e.g. Prytkova et al. 2025). Consequently, US investment trends provide an exogenous source of variation in the timing and intensity of technology diffusion across Europe. Second, exclusion: US technology investment should affect European regional labor markets only through the adoption of these technologies in Europe.[22] While European and US economies are exposed to similar global technology shocks, US investment decisions are unlikely to be directly affected by contemporaneous labor market conditions in individual European regions. Moreover, common demand shocks are controlled for by trade exposure. A more specific version of this concern is that US automation could displace European exports to the US through reshoring, affecting European labor markets directly rather than through European adoption; we probe this trade channel in Section 6.4 and find that it does not affect our estimates. This satisfies the exclusion restriction, as US investment acts as a supply-side shifter for European adoption rather than a reflection of regional labor demand.[23]

We construct the instrument by combining exogenous technological shifts in the US with the pre-determined industrial composition of European regions. Specifically, for each phase τ, we measure the change in US technology stocks—reflecting global supply-side innovation shocks—while fixing the regional employment structure at its 1980 levels. This yields the following shift–share instrument:

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

where $l_{ri,1980}$ is the share of employment in sector i in European region r in the base year 1980, and $Tech_{i,t}^{K,US}$ is the US stock of technology K per thousand workers in sector i at time t. The years t and $t+h$ mark the start and end of the investment phase τ, respectively.

This construction ensures that cross-regional variation in the instrument arises solely from historical industrial specialization within Europe, while the temporal variation is driven by exogenous technological shocks in the US. The resulting measure thus isolates plausibly exogenous exposure to global technology trends for each European region.

We use the following first-stage specification, estimated separately for each technology K

[22]A potential concern is that technology-driven wage or employment effects could induce European workers to emigrate to the United States, so that the instrument affects regional labor-market outcomes through population changes rather than through technology adoption. Such flows are far too small to threaten identification: gross legal permanent immigration from Europe to the United States averaged on the order of 80,000–95,000 persons per year over our sample period equivalent to roughly 0.02% of the EU population (over 440 million) (U.S. Department of Homeland Security, *Yearbook of Immigration Statistics*, https://ohss.dhs.gov/topics/immigration/yearbook/2023/table3). Moreover, our outcome is the employment-to-population ratio and observations are weighted by 1980 regional population, so changes in population are already netted out; for migration to bias the instrument it would, in addition, have to sort across regions in a manner correlated with the predetermined 1980 sectoral employment shares, which is highly implausible.

[23]Alternative approaches instrument European adoption with investment in other EU countries (Aghion et al. 2019; Dauth et al. 2021; Bachmann et al. 2022). However, cross-country employment trends within Europe are more tightly correlated due to shared institutions, supply chains, and labor mobility. Using US investment data thus provides a cleaner external instrument, less likely to transmit direct labor market effects to European regions.

and phase τ:

$$Exposure^{K}_{r,\tau} = \alpha + \beta_0 \times Exposure^{K,US}_{r,\tau} + \varepsilon_r, \tag{5}$$

where $Exposure^{K}_{r,\tau}$ is the observed (endogenous) exposure of European region r to technology K during phase τ, as defined in Equation (1), and $Exposure^{K,US}_{r,\tau}$ is the corresponding instrument constructed from US technological investment from Equation (4). The coefficient β_0 captures the strength of the relationship between US and European technology dynamics. A statistically strong estimate of β_0 confirms the instrument's relevance. The residual term ε_r captures unobserved regional heterogeneity in technology adoption not explained by global technological shifts.

Validity of the Instrument. It is important to assess the validity of the instrument, as a necessary condition for a causal interpretation is that the instrument is sufficiently strong and relevant in explaining variation in technology exposure. Tables C.7 to C.9 report the first-stage estimates for each technology and each investment phase. The instrument performs consistently well: first-stage coefficients are positive across all specifications, and the associated F-statistics indicate strong predictive power. For the full 1995–2017 period, the F-statistics are about 165 for robots, 49 for ICT, and 59 for SDB. Phase-specific estimates show similarly strong relevance. The weakest values occur for ICT in 2002–2005 (11.34) and 2005–2009 (10.79), and for SDB in 2002–2005 (12.65), yet all remain above the conventional threshold of 10. This confirms the validity of the instrument in each phase.

4.4 Analytical Framework

Table 1 outlines how we assess the net regional employment effect based on the estimated impact of technology exposure on both the employment-to-population ratio and the average wage. This matrix provides an interpretative framework for distinguishing between displacement, reinstatement, and skill substitution effects.

A positive effect on the employment-to-population ratio (first column) suggests a net creation of employment (reinstatement or demand expansion). This may result from the emergence of new tasks, occupations, or industries, or from a higher labor demand in existing ones, increasing the demand for human workers in the region. Workers may be sought within the industry adopting the technology (for instance, due to an increase in sales) or in other industries in the same region (for instance, creating demand for new services outsourced locally by adopting industries). We then infer the type of employment that is created based on the sign of the wage estimate (e.g., Diamond 2016; Shapiro 2006). When the regional average wage increases (decreases), this suggests that the employment creation is biased toward high-skilled

Table 1: Interpretation of the Net Employment Effects based on Estimates at the Regional Level

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

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

(low-skilled) workers. When the wage estimate is not significantly different from zero, we interpret this as an increase in employment of both types of labor in similar shares.[24]

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

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

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

5 Labor Market Impacts

In this section, we examine the results of our estimations of the impacts of exposure to robots, ICT, and SDB on the employment-to-population ratio and average wage. We first present the cumulative long-run effects (i.e., 1995–2017) to establish a baseline comparable to the existing literature. We then decompose these effects across the distinct phases of the technological life cycles identified in Section 3 — distinguishing between the early adoption phase (associated with early and majority adopters), and the maturity adoption phase (associated with late adopters). We also disaggregate the results at the sectoral level to identify which industries drive the results.

While we report OLS estimates for transparency (Tables C.1–C.6), our interpretation of the results focuses on the IV estimates, which address endogeneity concerns. Tables 2 and 3 present the IV results for the labor market impact of robots, ICT, and SDB in the long run (1995–2017) and for each phase of the technology life cycle. Each column corresponds to a different time period. The first column in each table shows the long-run effect (1995–2017) of a 1-SD increase in regional exposure to each technology on labor market outcomes. The remaining columns provide estimates for each phase of each technology life cycle.Panel A presents estimates for the employment-to-population ratio, while Panel B shows the effect on the average wage.

Table 2: IV Estimates of the Labor Market Impact of Robots during Robot Phases

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.09^{**}	0.19^{**}	0.03	-0.01	0.06^{*}
	(0.04)	(0.09)	(0.04)	(0.09)	(0.03)
R^2	0.65	0.75	0.94	0.71	0.83
Num. obs.	158	158	158	158	158
F statistic	14.20	23.41	120.35	19.12	36.88
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	0.01	-0.13	0.25^{**}	-0.12	0.32^{***}
	(0.13)	(0.22)	(0.11)	(0.25)	(0.12)
R^2	0.66	0.63	0.85	0.78	0.56
Num. obs.	158	158	158	158	158
F statistic	14.74	13.08	42.72	26.91	9.78

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the robot technology adoption life phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table 3: IV Estimates of the Labor Market Impact of ICT and SDB during Digital Technology Phases

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.03	0.35^{**}	-0.37^{**}	0.01	-0.10^{**}	-0.02
	(0.02)	(0.14)	(0.17)	(0.06)	(0.04)	(0.04)
SDB Exposure	-0.03^{*}	-0.27^{*}	0.17	-0.02	0.07^{*}	0.04
	(0.02)	(0.14)	(0.13)	(0.05)	(0.04)	(0.03)
R^2	0.65	0.75	0.71	0.81	0.91	0.83
Num. obs.	158	158	158	158	158	158
F statistic	14.20	23.41	18.65	32.01	74.22	36.88
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.23^{***}	-1.18^{***}	0.34	0.11	0.01	0.36^{*}
	(0.08)	(0.37)	(0.46)	(0.19)	(0.11)	(0.21)
SDB Exposure	0.26^{***}	1.00^{***}	0.11	0.13	0.03	0.20^{**}
	(0.07)	(0.27)	(0.31)	(0.19)	(0.10)	(0.09)
R^2	0.66	0.63	0.79	0.71	0.89	0.56
Num. obs.	158	158	158	158	158	158
F statistic	14.74	13.08	29.84	18.56	64.13	9.78

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table 4: IV Regression Estimates of the Sectoral Employment Impact of Robots during Robot Phases

	Δ Employment-to-population × 100					*Δ Average wage (in log) × 100*				
	All	Robotics			Intelligent Robots	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] *Agriculture*										
ROB Exposure	−0.00	−0.00	0.00	−0.03	−0.02***	0.14	−0.85	−0.03	−0.45	0.13
	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)	(0.46)	(1.40)	(0.70)	(1.33)	(0.73)
R^2	0.57	0.41	0.42	0.53	0.46	0.66	0.52	0.61	0.48	0.58
Num. obs.	158	158	158	158	158	153	154	153	153	153
F statistic	10.31	5.43	5.57	8.71	6.64	15.75	8.53	12.21	7.29	10.97
[B] *Industry*										
ROB Exposure	0.01	−0.00	−0.05***	0.07	0.02	0.21	0.01	0.30	0.30	0.19
	(0.02)	(0.03)	(0.02)	(0.05)	(0.01)	(0.15)	(0.43)	(0.28)	(0.41)	(0.16)
R^2	0.57	0.85	0.96	0.69	0.79	0.69	0.63	0.72	0.69	0.62
Num. obs.	158	158	158	158	158	155	155	155	155	155
F statistic	10.35	43.22	167.01	16.93	29.85	18.27	14.02	20.71	18.12	13.17
[C] *Services*										
ROB Exposure	0.08**	0.17**	0.09**	−0.05	0.08**	−0.00	0.06	0.25**	−0.28	0.28**
	(0.04)	(0.08)	(0.04)	(0.08)	(0.04)	(0.12)	(0.32)	(0.11)	(0.27)	(0.12)
R^2	0.70	0.61	0.84	0.75	0.66	0.73	0.69	0.83	0.66	0.60
Num. obs.	158	158	158	158	158	155	155	155	155	155
F statistic	17.81	12.32	39.70	23.47	15.19	21.38	18.15	38.87	15.72	12.04

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated IV regression coefficients for Agriculture (Panel A), Industry (Panel B), and Services (Panel C), over the robot technology adoption life cycle and phases. The outcome is the annualized change in the employment-to-population ratio (×100) in columns (1)–(5) and the annualized change in average wages (in log, ×100) in columns (6)–(10). Columns (1) and (6) are the long-difference estimates for the entire period (1995–2017). Columns (2)–(4) and (7)–(9) correspond to the three phases of the Robotics cycle. Columns (5) and (10) show the coefficients for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is constructed as a shift-share variable and standardized. Coefficients represent the change in the respective outcome variable for a one-standard-deviation increase in robot exposure during the cycle phase. Control variables include the log of the 1980 population, ICT and SDB exposure, the pre-trend in the respective outcome variable (annualized change over 1980–1994), final demand and trade exposure over the cycle phase, and country fixed effects.

Table 5: IV Regression Estimates of the Sectoral Employment Impact of ICT and SDB during Digital Technology Phases

	Δ *Employment-to-population* $\times$ *100*						Δ *Average wage (in log)* $\times$ *100*					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] *Agriculture*												
ICT Exposure	0.02*	0.02	0.01	0.01	−0.00	−0.01	0.04	0.58	−5.55**	−0.35	−0.07	−0.32
	(0.01)	(0.03)	(0.06)	(0.01)	(0.01)	(0.01)	(0.34)	(1.83)	(2.75)	(1.01)	(0.53)	(0.84)
SDB Exposure	0.00	0.00	−0.03	−0.01*	−0.01	−0.01	0.24	−2.39**	4.26***	−0.27	−0.08	0.14
	(0.01)	(0.02)	(0.05)	(0.01)	(0.00)	(0.01)	(0.42)	(1.19)	(1.54)	(0.69)	(0.51)	(0.48)
R^2	0.57	0.41	0.40	0.45	0.23	0.46	0.66	0.52	0.57	0.53	0.52	0.58
Num. obs.	158	158	158	158	158	158	153	154	154	153	153	153
F statistic	10.31	5.43	5.13	6.41	2.26	6.64	15.75	8.53	10.47	8.89	8.65	10.97
[B] *Industry*												
ICT Exposure	−0.01	−0.03	0.04	−0.02	−0.01	−0.01	−0.09	−0.37	1.01	0.27	−0.31**	−0.02
	(0.01)	(0.07)	(0.07)	(0.03)	(0.01)	(0.02)	(0.11)	(0.45)	(0.86)	(0.31)	(0.16)	(0.20)
SDB Exposure	−0.02	−0.01	−0.07	−0.03	−0.01	0.02	0.19*	0.34	−0.41	0.09	0.19	0.09
	(0.01)	(0.07)	(0.05)	(0.03)	(0.01)	(0.02)	(0.11)	(0.33)	(0.52)	(0.21)	(0.13)	(0.11)
R^2	0.57	0.85	0.73	0.88	0.93	0.79	0.69	0.63	0.71	0.50	0.78	0.62
Num. obs.	158	158	158	158	158	158	155	155	155	155	155	155
F statistic	10.35	43.22	20.88	57.13	105.85	29.85	18.27	14.02	19.40	7.91	28.57	13.17
[C] *Services*												
ICT Exposure	0.01	0.36***	−0.46**	−0.01	−0.08**	0.02	−0.15**	−1.01***	0.01	0.06	0.09	0.39*
	(0.02)	(0.09)	(0.20)	(0.05)	(0.04)	(0.05)	(0.07)	(0.33)	(0.67)	(0.19)	(0.12)	(0.23)
SDB Exposure	−0.01	−0.23***	0.33**	0.04	0.08**	0.02	0.22***	0.95***	0.20	0.23	−0.02	0.09
	(0.02)	(0.09)	(0.13)	(0.03)	(0.04)	(0.04)	(0.07)	(0.27)	(0.41)	(0.25)	(0.10)	(0.09)
R^2	0.70	0.61	0.67	0.66	0.79	0.66	0.73	0.69	0.73	0.42	0.87	0.60
Num. obs.	158	158	158	158	158	158	155	155	155	155	155	155
F statistic	17.81	12.32	15.75	15.28	29.88	15.19	21.38	18.15	22.09	5.78	53.00	12.04

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated IV regression coefficients for Agriculture (Panel A), Industry (Panel B), and Services (Panel C), over the digital technology adoption life cycle and phases. The outcome is the annualized change in the employment-to-population ratio ($\times 100$) in columns (1)–(6) and the annualized change in average wages (in log, $\times 100$) in columns (7)–(12). Columns (1) and (7) are the long-difference estimates for the entire period (1995–2017). Columns (2)–(3) and (8)–(9) correspond to the two phases of the Web 1.0 cycle; columns (4)–(5) and (10)–(11) correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; columns (6) and (12) correspond to the first phase of the Big Data and AI cycle. Exposure to information and communication technologies (ICT) and software and databases (SDB) are constructed as shift-share variables and standardized. Coefficients represent the change in the respective outcome variable for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the 1980 population, robot (ROB) exposure, the pre-trend in the respective outcome variable (annualized change over 1980–1994), final demand and trade exposure over the cycle phase, and country fixed effects. Regressions are weighted by the 1980 population.

5.1 Long-Run Impacts (1995–2017)

We confirm results from the literature that the long-run labor market effects differ markedly across technologies and are small.

Exposure to robots is associated with a positive effect on employment over the full period: a one–standard deviation increase in robot exposure leads to a 0.09 pp. annual increase in the employment-to-population ratio (Table 2, Panel A, Column (1)), corresponding to a cumulative increase of 2.07 pp. over 22 years. In contrast, the effect on regional average wages is statistically indistinguishable from zero (Table 2, Panel B, Column (1)). We interpret this pattern as suggesting that robot adoption does not systematically favor either low- or high-skilled workers in the aggregate, resulting in significant employment gains in highly exposed regions without detectable wage effects.

For ICT and Software–Database we find no statistically significant long-run effect on the employment-to-population ratio (Table 3, Panel A, Column (1)). In contrast, the two technologies exhibit opposite effects on average regional wages over the 1995–2017 period. A 1-SD increase in ICT exposure implies a 0.23% annual decline in average regional wages, whereas an equivalent increase in SDB exposure leads to a 0.26% annual increase (Table 3, Panel B, Column (1)). Following the interpretation framework summarized in Table 1, the combination of a null net employment effect and a significant wage response can be due to compositional changes in labor demand—i.e., a substitution between low and high-skilled workers. In particular, the positive wage effect associated with SDB exposure, coupled with unchanged employment rates, is consistent with a high-skill–biased effect of SDB, suggesting increased employment opportunities for high-skilled workers with higher wages, without net job creation. Conversely, the negative wage effect of ICT exposure in the absence of changes in the employment rate suggests a relative substitution away from high-skilled labor toward lower-paid jobs or a reinstatement of routine tasks. Overall, these results indicate that while ICT and SDB do not alter aggregate employment levels in the long run, they have meaningful and opposing implications for the skill composition of wages within regions.[25]

Sectoral Impacts (1995–2017)

We disaggregate these effects by sector in Tables 4 and 5. We find that the positive employment effect of robot exposure is primarily driven by job creation in services, while average wages re-

[25]For a different group of countries, including the US and UK, Michaels et al. (2014) find that industries investing in ICT are associated with an increase in demand for high-skilled. Importantly, their analysis is at the country-industry level—thus, it does not consider spillovers within regions—and does not include SDB, which complements ICT. We show that when we distinguish between ICT and SDB, it is the latter that drives the increase in demand for high skills. For a large set of European countries (2010–2019), Richiardi et al. (2025) show that workers with digital skills are more likely to find a job and see a growth in wage.

main largely unaffected. Notably, we find no evidence of a net employment effect within the sector that adopts most robots—namely, industry. The aggregate employment gains appear to stem from ancillary, largely non-tradable service sectors, consistent with indirect local demand spillover effects. These results echo the findings by Dauth et al. (2021) for German labor markets (1994–2014) that robot exposure caused job losses in manufacturing but offsetting job creation in services. Jestl (2024) also finds, for several European regions during a more recent period (2001–2016), that the positive effect of robots on employment occurs in service-intensive regions.[26]

For ICT and SDB we find no impact on the employment rate in the long run even disaggregating by sectors: no direct effect on services, and no spillovers on industry and agriculture (Table 5). The wage effects are largely driven by the service sector. Wage effects in agriculture and industry are generally weaker, with only marginal significance in industry. This sectoral pattern indicates that the opposing long-run wage effects of ICT and SDB identified at the aggregate level are primarily driven by services, where these technologies are most intensively used to enable low-skilled workers' activities (ICT) and complement high-skilled workers (SDB).

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

The null or moderate long-run effects documented above may mask substantial volatility across the technology life cycle. We now examine how labor market adjustments change from early adoption to maturity across technology life cycles using the same framework presented in Table 1.

Robots. Table 2 reports results for the two life cycles of robot technology: robotics and intelligent robots. The robotics cycle is further divided into the *early* phase (Column (2), 1995–2002), when early and majority adopters are more likely to invest, and the *maturity* phase (Column (4), 2007–2014), when late adopters are more likely to invest. In contrast to ICT and SDB, robot adoption exhibits an intermediate phase between 2002 and 2007 (Column (3)) in which the investment growth in this technology stagnates. For the recent breakthrough in intelligent robotics, we observe only the beginning of the first phase up to 2017.

We find that the long-run positive effect from robots' exposure is entirely driven by the *early* phase of their adoption. During the first phase of the robotics cycle (1995–2002), regions with a 1-SD higher exposure than average experienced an annual increase of the employment

[26]Our results are also in line with cross-country evidence by Graetz and Michaels (2018) from 17 countries showing no significant effect of robots on total employment. They differ from results by Chiacchio et al. (2018) that show a negative impact on employment rate, but only for six European countries and in the shorter period 1995–2007 (which covers two phases of the first technology life cycle).

rate of 0.19 pp, which is equivalent to a 1.33 pp. increase over the seven years of this early phase. This explains most of the 2.07 pp. increase observed over the entire period (1995–2017). During the following two phases of stagnant (2002–2007) and declining investment growth (2007–2014), we find no significant effect of robot exposure on the employment rate. This challenges the view that early automation is displacing; instead, the expansion phase appears to be labor-absorbing. During the intelligent robots cycle (2014–2017), we also find a positive impact on employment, though of a lower magnitude (0.06 pp. per year). However, it is important to note that the early phase of the intelligent robots cycle may not yet be complete, as our analysis is limited by data availability to 2017.

Turning to the effect on the average wage (Panel B), we find a positive effect during the 2002–2007 phase of the robotics cycle. In the context of the interpretation framework, rising wages with no employment growth suggest a substitution of low-skilled workers for high-skilled workers as the technology matures and low-skill tasks are increasingly automated. For the early phase of the intelligent robots cycle (2014–2017), we also find a positive and significant coefficient, suggesting that the employment gains from this technological breakthrough primarily benefit high-skill workers rather than low-skill ones.

ICT and Software–Database. Table 3 shows that the muted long-term impact on the employment rate is a result of offsetting effects during different phases of the technology life cycle. A 1-SD increase in regional exposure to ICT is associated with a 0.35 pp. annual increase in the employment rate during the early phase of the Web 1.0 cycle (1995–2002). This is akin to a substantial 2.45 pp. increase in the employment rate in those highly exposed regions during these seven years. This effect is reversed during the maturity phase of the technology life cycle (2002–2005) when a 1-SD increase in exposure is associated with a similar 0.37 pp. annual decline in the employment rate. The 1.18% annual decrease in wages during the early phase (1995–2002) and the positive (but non-significant) effect during the second phase (2002–2005) indicate that the employment-to-population growth during the first phase is mainly among the low-skilled, whereas the decline is not skill-biased. The second cycle, characterized by the breakthrough of GUI and cloud computing, shows a similar but more muted pattern. A 1-SD increase in regional exposure to ICT is associated with a small (but not significant) increase in the employment rate during the early phase (2005–2009) and a 0.1 pp. decline during the second phase of the same cycle (2009–2014). In both phases, we find no significant effect on the average wage.

As noted in our discussion of the long-run impacts, exposure to ICT and SDB tend to engender opposite effects on wages. This is also the case for the employment-to-population ratio. Specifically, SDB exhibits immediate displacement effects in the early phase, contrasting with the employment expansion of ICT. A 1-SD increase in regional exposure to SDB is associated with a 0.27 pp. annual decline in the employment rate during the early phase of the Web 1.0 cycle (1995–2002). We find the opposite sign during the maturity phase of the technology life cycle (2002–2005), but in the case of SDB, the effect is not statistically significant. The 1% annual increase in wages during the early phase (1995–2002) and the positive (but non-significant) effect during the second phase (2002–2005) suggest that the employment cuts during the first phase are mainly among the low-skilled. Also for SDB, the second breakthrough (GraphUI – Cloud) shows a similar but more muted pattern (balancing the effect of ICT). A 1-SD increase in regional exposure to SDB is associated with a small and not significant decline in the employment rate during the early phase of that cycle (2005–2009) and a 0.07 pp. increase during the second phase of the same technology breakthrough (2009–2014). In both phases, we find no significant effect on the average wage.

Finally, the first phase of the third technology life cycle (Big Data – AI, 2014–2017) shows a different pattern. Employment effects for both technologies flip sign with respect to the first phase of the two previous cycles (but coefficients are small and not significant), and the impact on wages is positive for both ICT and SDB. As noted above, due to data limitation we observe only the beginning of the first phase of this third cycle, and we do not know yet when it finishes. These preliminary results suggest that both tangible and intangible digital technologies are skill-biased in the current AI-driven wave, contrasting with the low-skill reinstatement observed in the earlier ICT hardware wave.

5.3 Implications for the Technology Life Cycle Theory

Our results provide new evidence on how recent waves of digital and automation technologies (i.e., robots, ICT, and SDB) affect labor markets over the technology life cycle. Existing theories, largely developed in the context of earlier ICT revolutions, emphasize that employment and skill effects evolve over time as technologies diffuse and mature. In particular, early contributions predict that initial adoption is skill-biased, as firms rely on highly educated workers to integrate new technologies and exploit their productivity potential (Bartel and Lichtenberg 1987; Aghion 2002). Building on the routine-biased technical change framework, Vona and Consoli (2015) formalize this intuition into a technology life-cycle model with three broad stages. In the early phase, adoption depends on tacit knowledge held by a small group of skilled workers; as learning progresses, tasks become standardized, increasing substitutability between labor and technology; and in the maturity phase, displacement of routine and middle-skill workers becomes more pronounced.

Our findings both corroborate and refine these predictions, also highlighting the distinction between tangible and intangible technologies. We find evidence of skill-biased adjustment in the early phase of the technology life cycle for intangible technologies such as SDB, but not for ICT or robots. For SDB, regions more exposed during early diffusion experience rising average wages alongside declining employment rates, consistent with substitution toward fewer but more skilled workers. This pattern is particularly pronounced during the first digital cycle (Web 1.0), aligning closely with canonical skill-bias predictions.

In contrast, ICT adoption since 1995 deviates from the standard early-phase skill-bias narrative. We find that early ICT diffusion is associated with net employment gains, particularly among lower-paid workers, with no corresponding increase in average wages. These effects are concentrated in the initial phase of the technology cycle, suggesting that productivity-driven demand expansion—potentially through complementary services, installation, maintenance, and downstream activities—dominates substitution effects at this stage. This pattern is consistent with models emphasizing demand spillovers and labor hoarding during the early integration of general-purpose technologies.

For robots, we detect neither employment displacement nor clear changes in skill composition during the early adoption phases of both robot cycles. This finding challenges a mechanical interpretation of early automation as immediately skill-biased and instead points to the importance of adjustment frictions. Firms may require time to reorganize production, redesign tasks, and accumulate complementary capabilities before automation technologies translate into labor substitution (Domini et al. 2021).

The maturity phase of the technology life cycle exhibits stronger alignment with theoretical predictions. For ICT, we observe net employment displacement as diffusion progresses, consistent with rising substitutability between labor and technology (as in Reljic et al. 2021). Wage effects in this phase are positive but imprecisely estimated, which may reflect limitations of average wages as a proxy for task-level skill intensity. For robots, employment declines emerge during the transition to maturity (2002–2007), accompanied by modest wage increases, again suggestive of labor substitution concentrated among more automatable tasks. In contrast, SDB adoption in the mature phase is associated with employment growth, consistent with firms realizing productivity gains from earlier organizational restructuring and reallocating labor toward complementary activities.

Taken together, our results confirm that employment effects of automation and digital technologies vary systematically across both technologies and life-cycle phases. They support the central insight of the technology life-cycle framework—that displacement tends to occur after an initial period of learning and adaptation—while highlighting important heterogeneity across technologies (Cirillo et al. 2024; Jestl 2024). In particular, our findings suggest that skill bias is neither universal nor confined to early adoption. Instead, it depends critically on the nature of the technology: intangible, information-based technologies such as SDB more closely follow the canonical skill-biased life-cycle pattern, whereas tangible technologies such as ICT hardware and robots exhibit weaker early skill bias and stronger displacement effects only as adoption matures. Overall, these results imply that theories of technology and employment must account not only for diffusion timing but also for technological characteristics that shape how firms reorganize production and adjust labor demand over time.

6 Validity and Robustness Checks

The empirical findings presented above are based on an IV estimation strategy designed to mitigate potential endogeneity concerns. In this section, we assess the validity of our identification strategy and examine the robustness of our results to the joint entry of ICT and SDB exposure, alternative shift-share instrument constructions, pre-existing trends, and the timing of technology life-cycle phases. We also verify that the qualitative findings are not driven by fixing sectoral employment shares in 1980 rather than in a later pre-period year: the appendix reports a 1990-share robustness check that preserves the main patterns.

6.1 Digital Technologies: ICT and SDB

Throughout the analysis, we treat ICT and SDB as two distinct but complementary components of digitalization, and we enter their regional exposures jointly in the digital-technology regressions (Table 3). Because the two share a common periodization and tend to be adopted together, one might worry that they are too correlated to be separately identified, and that either a single combined digital measure or a one-at-a-time specification would be preferable. We show that this is not the case: ICT and SDB are complementary rather than redundant, and only the joint specification recovers their distinct labor-market roles.

We first document their co-occurrence. Across regions, standardized ICT and SDB exposures are positively but far from perfectly correlated (0.56), and the corresponding instruments correlate at 0.86 (Appendix Figure D.1). This positive co-movement is consistent with complementary adoption—regions that invest in communication and information hardware also tend to invest in software and databases—but it remains well below the range that would preclude separate identification.

Joint entry does not weaken identification. The Sanderson–Windmeijer conditional first-stage F-statistics, which test whether each endogenous regressor is separately identified given the others, are large for both technologies (35.4 and 38.0 for ICT; 37.7 and 38.6 for SDB, across the two outcomes) and comfortably exceed conventional weak-instrument thresholds (Appendix Table D.1). Each digital technology is therefore strongly and separately instrumented even when the two enter together.

The joint specification is also the informative one. Collapsing ICT and SDB into a single combined measure (DIG = ICT + SDB) yields effects that are essentially flat—close to zero and statistically insignificant for both employment and wages over the full period (Appendix Table D.3). Entering the technologies one at a time is equally uninformative: the significant and opposing full-period wage effects estimated jointly (a 0.23% annual decline for ICT and a 0.26% annual increase for SDB; Table 3) both attenuate to insignificance when either technology is entered alone (Appendix Tables D.4 and D.5). Both alternatives blur the two technologies' offsetting contributions precisely because ICT and SDB are complementary and co-adopted. We therefore retain the joint specification, which is well identified and, unlike the combined or one-at-a-time alternatives, disentangles the distinct roles of the two digital technologies.

6.2 Rotemberg Weights

Following Goldsmith-Pinkham et al. (2020), we assess the validity of our Bartik instrument by making explicit the implicit weighting structure of the IV estimator. Specifically, we decompose the aggregate 2SLS coefficient into Rotemberg weights (α_k) and just-identified estimates (β_k), where α_k captures how much each country–industry pair drives identification and β_k is the estimate that pair alone would deliver. This decomposition serves two diagnostic purposes. First, it reveals whether identification is concentrated in a small number of influential pairs, and it checks whether the pair-specific estimates are mutually consistent rather than averaging over heterogeneous local effects. After doing this, we find that across all three technologies, the dominant instruments—German manufacturing for robots, Spanish information and communication sectors for ICT, and French financial and business services for SDB—produce just-identified estimates that cluster tightly around the aggregate IV coefficient, and excluding the regions associated with the highest weights leaves results unchanged. Full details, including summary tables of the five most influential country–industry pairs, scatter plots of α_k against β_k, and exlusion regressions are reported in Appendix D.

6.3 Pre-Trends

Another concern for the validity of our instrumental-variable strategy is whether regions more exposed to technological change—based on their 1980 sectoral employment structure—were already on different trajectories before the period in which we observe adoption. If pre-existing trends in employment or wages correlate with exposure predicted by the historical composition, the instrument may partly capture structural forces unrelated to technology adoption, undermining the exclusion restriction (Acemoglu and Restrepo 2020). Testing for such pre-trends, therefore, provides an additional validation of the identifying assumption.

Table D.12 reports estimates of the relationship between exposure to each technology and pre-period outcomes (1980–1994), alongside benchmark estimates for the post-period (1995–2017).[27]

For robot exposure, we find no evidence of a pre-trend in employment: regions that would later be more exposed to robots do not exhibit differential employment dynamics prior to 1995, supporting the exogeneity of the robot instrument for our main employment outcome. Robot exposure is associated with a negative pre-period wage trend, but this does not persist into our sample period—the post-1995 wage effect is statistically indistinguishable from zero—so it does not threaten our interpretation.

By contrast, the point estimates for ICT and SDB indicate some pre-existing trends. ICT exposure is positively and significantly associated with pre-period employment growth, while SDB exposure is positively associated with pre-period wage growth. These patterns warrant caution in interpreting the post-1995 effects, and they are consistent with the historical evolution of the ICT sector. As discussed in Section 3, the ICT revolution began well before 1995, such that regions with a structural orientation toward ICT-intensive sectors may already have been experiencing different labor market dynamics before our main analysis window.

To mitigate concerns that these pre-trends drive the post-1995 results, we have included the change in the relevant outcome variable over 1980–1994 as a control in our baseline specification. This pre-period change captures latent regional dynamics correlated with early technology diffusion. Comparing columns (2) and (3) of Table D.12 shows the role of these pre-trends.

For employment, the positive effect of ICT exposure observed in column (2) disappears once we control for pre-period employment changes. This suggests that the earlier differential trajectories were responsible for the initial positive estimate.

For wages, however, the estimated effects of ICT and SDB remain stable after conditioning on pre-period wage growth. Despite the presence of a pre-trend for SDB, the post-1995 wage estimates appear robust to the inclusion of the pre-period outcome, indicating that the causal interpretation is not compromised by earlier differential wage dynamics.

For transparency, we also report the baseline estimates without this control in Tables D.13 and D.14. Overall, the qualitative patterns are robust to this adjustment.

For robots, the estimated effects across technology life-cycle phases remain largely un-

[27] Data for imports and real consumption are unavailable before 1995; regressions for 1980–1994 thus exclude these controls. This explains the differences between columns (2) and (3) in Table D.12 and the baseline estimates in Table 3.

changed. The only exception is the employment effect in the 2014–2017 cycle phase, which is statistically significant in the baseline but loses significance once the pre-period employment control is removed.

For ICT and SDB, the main difference arises in the first phase of the 1995–2002 cycle, where the estimated employment effects are larger when pre-trends are not controlled for. This pattern is consistent with the presence of residual effects from earlier waves of ICT-related innovation prior to our sample period. Once pre-period outcome changes are included, these early-phase effects attenuate, while the estimates for later phases remain stable in both sign and magnitude.

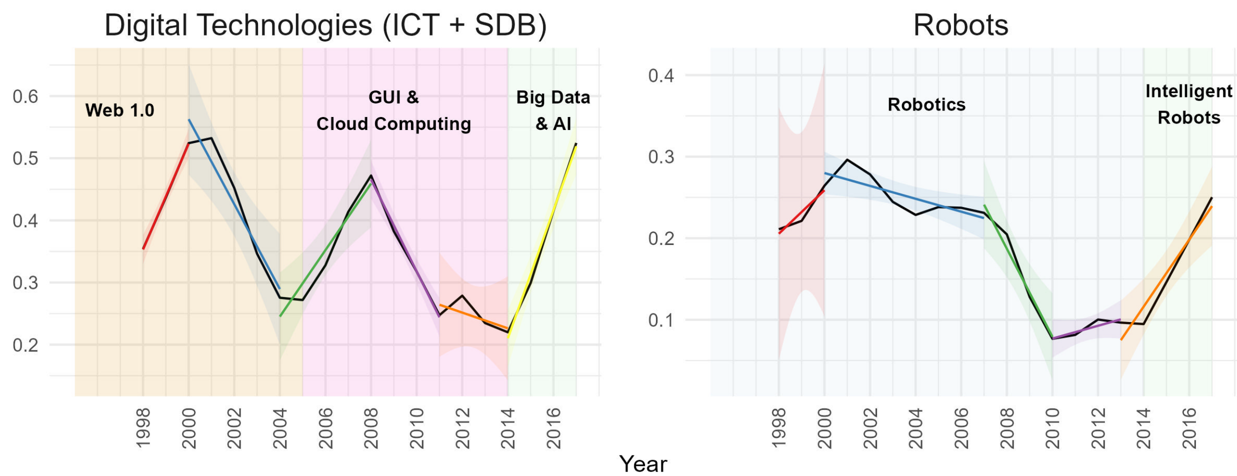
6.4 Trade Exposure and Reshoring

Our identification requires that US technology investment affects European labor markets only through European technology adoption, and not through an independent trade channel. One such channel is automation-induced reshoring: US automation could lower US production costs and displace European exports to the US, affecting European employment and wages directly. Because exposure to this channel depends on regional industrial specialization, it need not be absorbed by our country fixed effects or by the existing control for Chinese import competition.

We assess this concern in two ways, reported in Appendix D. First, we re-estimate the main specifications after excluding the quartile of regions most dependent on the US export market in 1995, where the reshoring channel should be strongest. Second, we augment the baseline with regional shift–share measures of bilateral trade exposure to the United States (exports to and imports from the US), constructed analogously to the Chinese-import control. The estimates, reported in Tables D.17 and D.18, are essentially unchanged when the US-trade controls are added, and they preserve the sign and phase pattern of the baseline when the most US-export-dependent regions are excluded. We therefore find no evidence that automation-induced reshoring drives our results.[28]

[28]We conducted an additional check adding Eastern European trade exposure. That is, we retain imports from China as our baseline trade control, and we include regional shift-share measures of bilateral trade with ten Eastern European economies constructed per 1980 worker exactly as for the Chinese-import control. Tables D.15 and D.16 show the results including trade exposure from Eastern Europe. Long-run and short-run results remain largely unchanged, confirming that our estimates are not driven by the omission of Eastern European trade competition.

Figure 3: Investment Cycles Between 1995 and 2017 (Alternative Approach Using First-Difference)



Notes: This figure illustrates the investment cycles in digital technologies and robots using the first-differenced series. We first extract cyclical components by regressing the three-year moving average of the first difference of each technology stock on a linear time trend, controlling for real consumption to account for business cycle fluctuations. We then apply a simultaneous multiple-breakpoint estimation procedure, following Bai and Perron (2003), to each differenced technology series in order to partition it into m distinct cycles (i.e., segments).

6.5 Breakpoint Sensitivity

A potential challenge to our results on the technology life cycle is that our results are sensitive to the precise timing of the structural breakpoints used to define its phases. In the baseline specification, these breakpoints are obtained using the algorithm of Bai and Perron (2003) applied to residualized technology stock series after removing a time trend and aggregate demand effects. To assess the robustness of our findings to this modeling choice, we conduct a sensitivity analysis based on an alternative breakpoint construction.

Specifically, instead of applying the breakpoint algorithm to residualized levels of technology stocks per capita, we apply Bai and Perron (2003) to the first differences of each technology stock per capita. This approach identifies breaks directly in investment growth rates, rather than in deviations from long-run trends. Figure 3 illustrates the resulting cycle phases under this alternative procedure.

Overall, the inferred cycle phases are remarkably similar across the two approaches. For robots, the alternative method places the phase transitions slightly earlier—around 2000 rather than 2002 for the first peak, and 2010 rather than 2014 for the onset of the final phase—effectively absorbing the short plateau observed in the baseline classification into the subsequent decline. For digital technologies (ICT and SDB), both methods yield the same number of phases, and the timing of the breaks is nearly identical. The main difference is that the decline in investment growth following the first expansion begins in 2000 (rather than 2002) under the first-difference approach.

This discrepancy is consistent with the underlying methodology. Our preferred approach explicitly controls for aggregate demand conditions, allowing it to attribute the post-2000 slowdown in digital investment to the bursting of the dot-com bubble. In contrast, the first-difference approach does not purge demand-driven fluctuations and therefore identifies the peak somewhat later. The close correspondence between the two sets of breakpoints nonetheless suggests that the estimated cycle phases are not an artifact of the specific detrending procedure.

Re-estimating the main specifications using the alternative breakpoints yields very similar results (Tables D.25 and D.26). For ICT and SDB, both the magnitude and the sign of the estimated effects remain virtually unchanged across cycle phases. For robots, the only notable difference concerns the employment effect in the final phase: while positive and statistically significant in the baseline specification (2014–2017), it becomes smaller and statistically insignificant when the final phase is expanded to 2010–2017 under the alternative classification. This attenuation likely reflects the inclusion of earlier years in which robot adoption was less strongly associated with employment gains.

Overall, this sensitivity analysis indicates that our conclusions are not driven by the precise timing of the structural breaks used to define technology life cycles. The main patterns are robust across alternative breakpoint identification of the life cycle of these technologies. This reinforces our interpretation that the estimated effects reflect genuine phase-dependent responses rather than spurious artifacts of the segmentation procedure.

7 Conclusion

This paper provides an empirical test of theories predicting differentiated impacts of digital and automation technologies along their Technology Life Cycle (TLC). While canonical models often treat automation as a uniform shock, TLC theory predicts that the labor market consequences of new technologies change as technologies transition from experimental adoption to standardization. Using data for 158 NUTS-2 regions across 12 European countries between 1995 and 2017, we identify distinct technological breakthroughs and corresponding phases of rapid and decelerating investment. We interpret these phases as early and mature stages of technology adoption and study their labor market implications for employment and wages. To address endogeneity in regional exposure, we employ a shift–share instrumental-variable strategy that leverages U.S. investment dynamics as an external source of variation.

Our analysis yields four main findings that refine our understanding of how technology reshapes labor demand. First, we find that the early phase skill bias predicted by theory holds for intangible digital technologies such as software and databases (SDB). Exposure to SDB is associated with declining employment and rising wages during early adoption, consistent with early substitution toward higher-skilled workers. In contrast, tangible technologies exhibit different dynamics: ICT adoption in its early phase is associated with the reinstatement of lower-paid jobs, while robots display largely skill-neutral effects during early diffusion. These results highlight that early-stage labor market effects depend critically on the nature of the technology.

Second, we show that the labor market effects of ICT and robots are concentrated in the first technology vintage—Web 1.0 for digital technologies and the initial robotics wave—roughly between 1995 and the mid-2000s. Subsequent technological breakthroughs exhibit more muted employment and wage responses.

Third, ICT and SDB exert opposing labor market effects. ICT adoption tends to expand employment—particularly among lower-paid workers—during early diffusion, whereas SDB adoption is associated with labor displacement and higher wages. In regions where both technologies diffuse in tandem, these opposing forces largely offset each other, resulting in limited net employment effects.

Fourth, we show that labor market adjustments occur primarily through the service sector. Although robots are predominantly adopted in manufacturing, their positive regional employment effects materialize mainly in services. This finding validates the importance of general equilibrium effects at the regional level: productivity gains in tradable sectors increase local aggregate demand for non-tradable services. It also underscores the relevance of sectoral reallocation in understanding the employment consequences of automation and digitalization.

These findings carry several policy implications. Employment impacts vary sharply across technologies and stages of adoption, implying that "one-size-fits-all" responses to automation are unlikely to be effective. Targeted interventions may be particularly important during phases associated with short-term displacement—such as the maturity phase of ICT adoption and the early phase of SDB diffusion. If the diffusion of AI follows the trajectory of intangible capital, policymakers should anticipate immediate skill-biased displacement, rather than the "reinstatement". Moreover, the persistent wage effects associated with ICT adoption raise concerns about regional wage inequality, highlighting the role of labor market institutions and active labor market policies, including retraining and skill upgrading, in facilitating adjustment.

Our study also has limitations that point to avenues for future research. The absence of granular data on firm-level adoption constrains our ability to capture within-region heterogeneity in diffusion patterns and adjustment dynamics. Future work using harmonized firm- and worker-level data could shed light on how early and late adopters within regions respond differently to technological change and whether task-level reallocation underlies the aggregate patterns documented here. Further research could also explore spatial spillovers and labor mobility across regions, as well as the interaction between technology adoption, regional specialization, and migration. Finally, our sample ends in 2017 and therefore predates the recent wave of generative AI and large language models. As this technology is still in its investment-expansion phase, whether our life-cycle findings extend to it remains an open question that we leave to future research.

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Appendices

A Data

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

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

Table A.1: Sectors of Economic Activities and NACE Sections

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

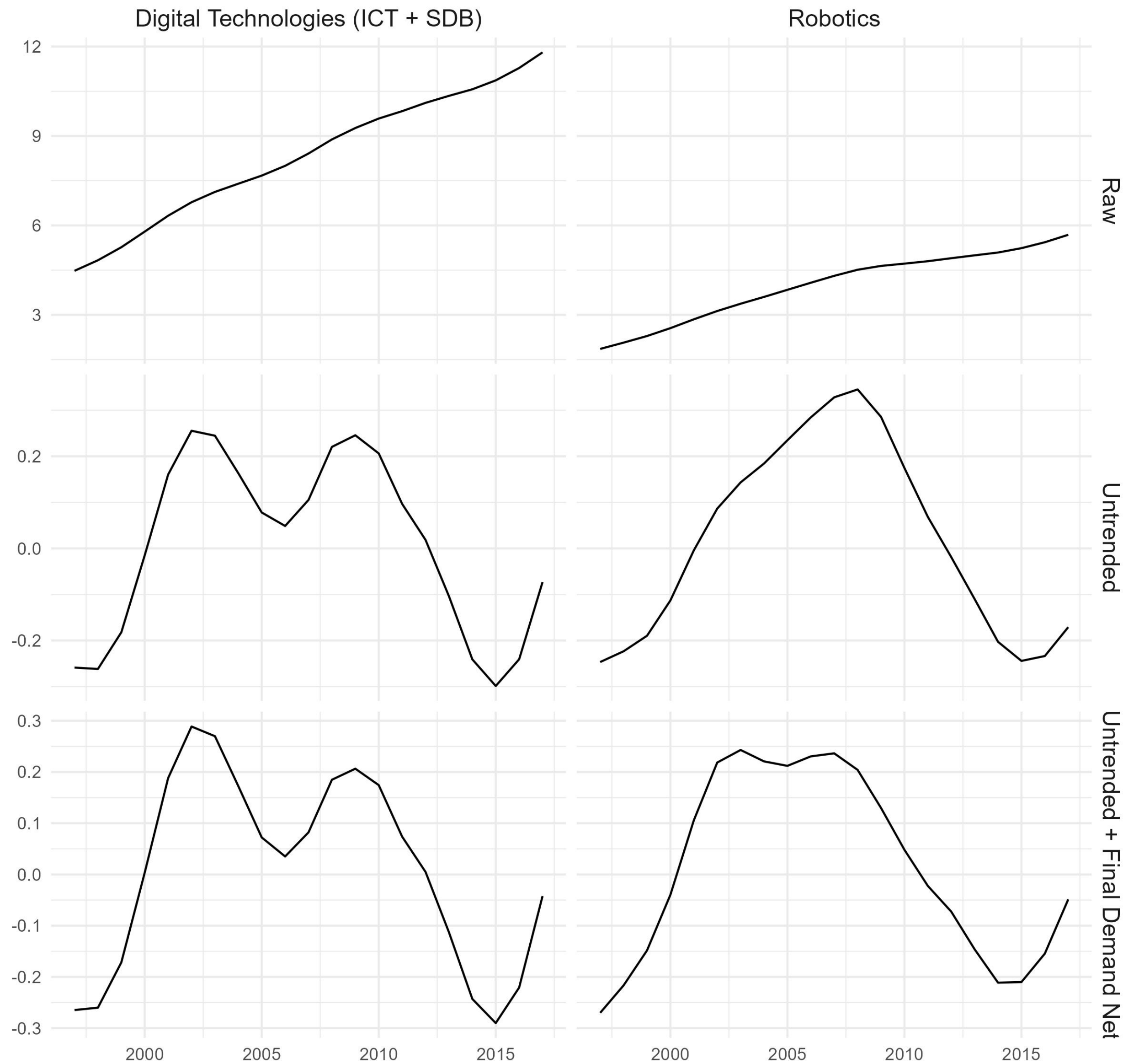
Notes: This table presents the classification of 1-digit NACE industries into sectors used in the analysis. The classification is derived from the NACE classifications to be compatible across the two versions, Rev. 1.1 and Rev. 2. Table A.2 summarizes both NACE classifications in the appendix.

Table A.2: Overview of NACE Classifications

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

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

Figure A.1: Technology Stocks per Thousand Workers in 1980 (3-Year Moving Average)



Notes: This figure shows the evolution of the technology stock per thousand workers in 1980, aggregated for the 12 European countries in the sample. Raw panels refer to the series in level. Untrended panels display the residuals after regressing the raw time series on a linear time trend, and the last row of panels shows the residuals after controlling for real consumption (to account for business cycles).

B Descriptive Statistics

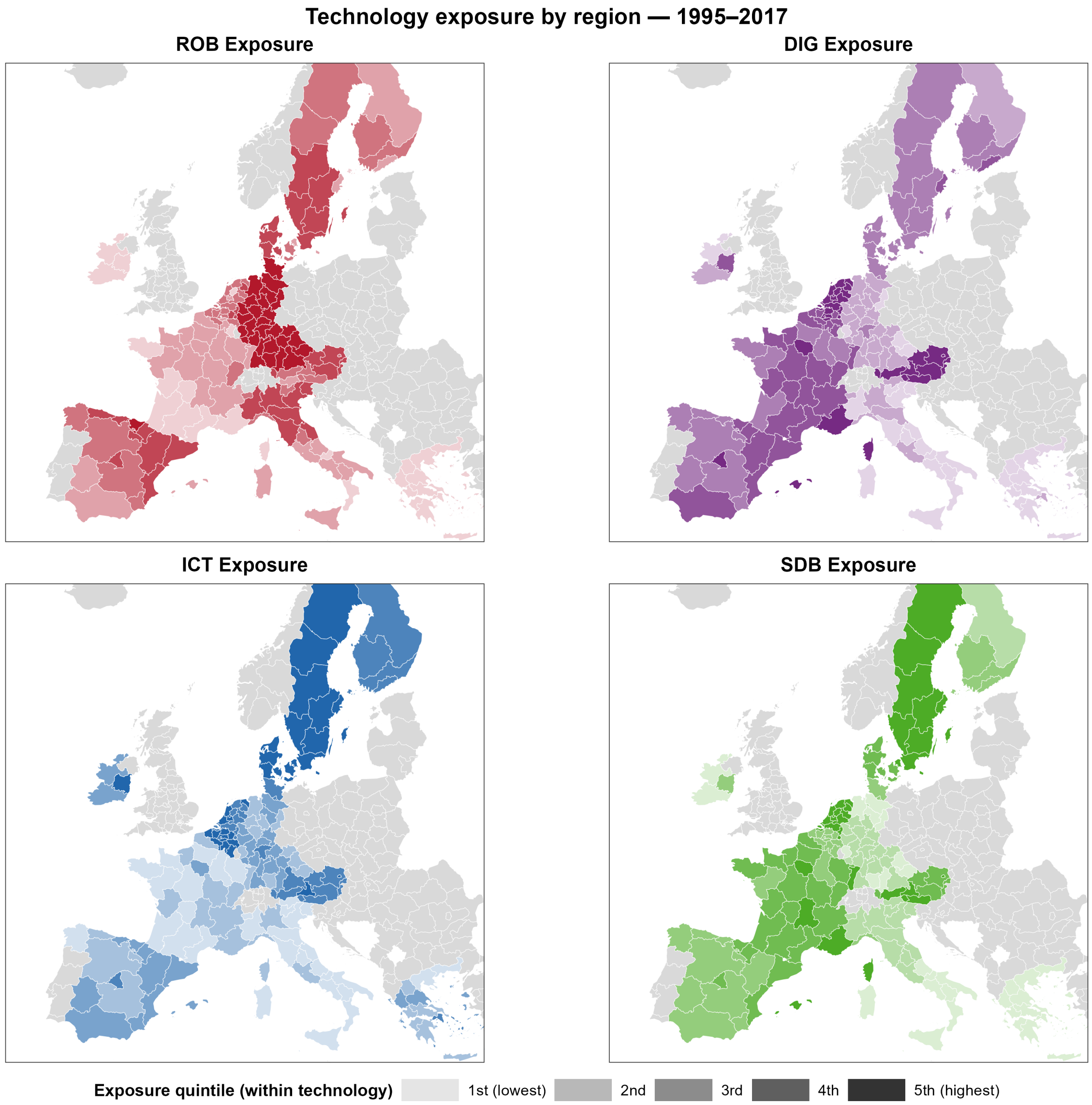
Table B.1 shows the summary statistics of the change in the outcome variables, in the technology stock (per thousand workers in 1980), as well as in imports and final demand, over the whole period of analysis (1995–2017).

Table B.1: Summary Statistics of Long Run Change in Variables (1995–2017)

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

Notes: This table shows the summary statistics of the change in the outcome, independent, and control variables for the 158 NUTS-2 regions between 1995 and 2017. Outcomes variables are employment-to-population ratio (Emp-to-pop. ratio)—measured as the total number of employed persons aged 15-64 over the total population—, average yearly wage per worker (Wage) in thousands euros of 2015—calculated as the ratio between total labor compensation and the level of employment. All outcome variables are annualized (i.e., 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), information and communication technology (ICT), and software and database (SDB). Data are from the IFR for robots and EU-KLEMS for the rest. Control variables are imports—measured as imports from China using the OECD Trade in Value Added database—and final demand—measured as the real consumption index from the Inter-Country Input-Output database.

Figure B.1: Regional Exposure to Automation Technologies (1995–2017)



Notes: Each panel maps long-run (1995–2017) shift-share exposure of the 158 NUTS-2 regions to one technology—robots (ROB), the combined digital measure (DIG = ICT + SDB), ICT, and software and databases (SDB). Because raw exposure scales differ across technologies, each panel is shaded by within-technology quintiles (1st = lowest, 5th = highest), so the panels are comparable in their ranking but not in their cross-technology levels. Regions outside the estimation sample are shown in grey.

C Regression Tables

C.1 OLS Regressions

Aggregate Impact. Table C.1 presents the OLS estimates of the effect of robots on the employment-to-population ratio and the average wage during their respective technology life cycle phases. Table C.2 provides the OLS estimates for the effects of ICT and SDB separately.

Table C.1: OLS Estimates of the Labor Market Impact of Robots during Robot Phases

	OLS Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* × *100*					
ROB Exposure	0.09^{*}	0.20^{**}	0.11	-0.04	0.07
	(0.05)	(0.08)	(0.07)	(0.09)	(0.05)
R^2	0.64	0.75	0.94	0.71	0.82
Num. obs.	158	158	158	158	158
F statistic	13.94	22.78	118.44	18.76	35.15
[B] Δ *Average wage (in log)* × *100*					
ROB Exposure	0.13	0.13	-0.08	-0.12	-0.03
	(0.20)	(0.26)	(0.20)	(0.25)	(0.16)
R^2	0.64	0.62	0.84	0.77	0.54
Num. obs.	158	158	158	158	158
F statistic	13.95	12.42	40.22	26.36	8.96

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.2: OLS Estimates of the Labor Market Impact of ICT and SDB during Digital Technology Phases

	OLS Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.07	0.16^{***}	0.20	0.08	−0.03	0.02
	(0.06)	(0.06)	(0.16)	(0.09)	(0.14)	(0.09)
SDB Exposure	−0.00	0.08	-0.27^{*}	0.11	0.02	0.02
	(0.06)	(0.10)	(0.16)	(0.07)	(0.06)	(0.10)
R^2	0.64	0.75	0.71	0.81	0.90	0.82
Num. obs.	158	158	158	158	158	158
F statistic	13.94	22.78	19.00	33.63	69.92	35.15
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.28^{*}	−0.08	−0.05	−0.23	0.40	−0.20
	(0.16)	(0.37)	(0.21)	(0.28)	(0.27)	(0.28)
SDB Exposure	0.06	−0.78	0.40	0.23	−0.19	0.77^{*}
	(0.38)	(0.55)	(0.32)	(0.27)	(0.16)	(0.45)
R^2	0.64	0.62	0.79	0.70	0.87	0.54
Num. obs.	158	158	158	158	158	158
F statistic	13.95	12.42	28.51	18.03	51.68	8.96

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Sectoral Impact. Tables C.3 and C.4 summarize the OLS estimates of the effects of robots on the employment-to-population ratio and the average wage by sector during the robot life cycle phases. Tables C.5 and C.6 provide the OLS estimates of the employment and wage effects, respectively, for both ICT and SDB during digital technology life cycle phases.

Table C.3: OLS Estimates of the Sectoral Employment Impact of Robots during Robot Phases

	OLS Reg. – Dep. var.: Annualized Δ Employment-to-population $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] *Agriculture*					
ROB Exposure	-0.02	0.01	-0.01	-0.05^{**}	-0.01
	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
R^2	0.58	0.43	0.43	0.54	0.45
Num. obs.	158	158	158	158	158
F statistic	10.53	5.72	5.73	9.03	6.29
[B] *Industry*					
ROB Exposure	0.04^{*}	0.05	0.04	-0.01	0.02
	(0.02)	(0.03)	(0.03)	(0.04)	(0.02)
R^2	0.57	0.86	0.96	0.68	0.80
Num. obs.	158	158	158	158	158
F statistic	10.08	46.46	165.48	16.19	30.00
[C] *Services*					
ROB Exposure	0.05	0.10	0.08	-0.01	0.08
	(0.06)	(0.08)	(0.08)	(0.07)	(0.06)
R^2	0.69	0.58	0.82	0.73	0.65
Num. obs.	158	158	158	158	158
F statistic	16.87	10.88	34.35	21.37	14.39

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized change in employment-to-population ratio in Agriculture (Panel A), Industry (Panel B), and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the emp-to-pop in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects.

Table C.4: OLS Estimates of the Sectoral Wage Impact of Robots during Robot Phases

	OLS Reg. – Dep. var.: Annualized Δ Average wage (in log) $\times$ 100				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] *Agriculture*					
ROB Exposure	-0.96^{*}	-2.32^{**}	-0.56	0.17	-0.63
	(0.52)	(1.15)	(1.04)	(1.82)	(1.22)
R^2	0.68	0.51	0.61	0.50	0.58
Num. obs.	153	154	153	153	153
F statistic	16.68	8.42	12.49	7.82	11.12
[B] *Industry*					
ROB Exposure	-0.04	0.11	0.10	0.25	0.36^{*}
	(0.21)	(0.40)	(0.46)	(0.46)	(0.21)
R^2	0.68	0.64	0.72	0.69	0.63
Num. obs.	155	155	155	155	155
F statistic	17.20	14.13	20.32	18.31	13.57
[C] *Services*					
ROB Exposure	0.12	0.45	-0.14	-0.40^{*}	0.04
	(0.17)	(0.28)	(0.19)	(0.23)	(0.15)
R^2	0.71	0.68	0.82	0.67	0.60
Num. obs.	155	155	155	155	155
F statistic	20.16	16.83	36.37	16.64	12.21

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized log-change in average wage in Agriculture (Panel A), Industry (Panel B), and Services (Panel C) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the average wage in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects.

Table C.5: OLS Estimates of the Sectoral Employment Impact of ICT and SDB during Digital Technology Phases

	OLS Reg. – Dep. var.: Annualized Δ Employment-to-population $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] *Agriculture*						
ICT Exposure	0.02^{*}	0.04^{**}	0.08^{*}	0.01	-0.03^{*}	-0.00
	(0.01)	(0.02)	(0.04)	(0.03)	(0.02)	(0.01)
SDB Exposure	0.03^{**}	0.04	-0.03	0.03	0.00	-0.04
	(0.01)	(0.03)	(0.03)	(0.02)	(0.01)	(0.02)
R^2	0.58	0.43	0.42	0.45	0.23	0.45
Num. obs.	158	158	158	158	158	158
F statistic	10.53	5.72	5.57	6.33	2.36	6.29
[B] *Industry*						
ICT Exposure	-0.01	0.07	0.10^{*}	-0.06	0.12^{***}	0.04^{**}
	(0.02)	(0.04)	(0.06)	(0.06)	(0.03)	(0.02)
SDB Exposure	-0.04	-0.14^{**}	-0.14^{**}	-0.05	-0.01	-0.01
	(0.03)	(0.06)	(0.06)	(0.05)	(0.02)	(0.03)
R^2	0.57	0.86	0.74	0.88	0.94	0.80
Num. obs.	158	158	158	158	158	158
F statistic	10.08	46.46	21.55	56.08	116.65	30.00
[C] *Services*						
ICT Exposure	0.03	0.01	-0.01	0.10	-0.11	-0.01
	(0.06)	(0.08)	(0.10)	(0.07)	(0.16)	(0.07)
SDB Exposure	0.01	0.28^{**}	-0.10	0.14^{**}	0.02	0.09
	(0.07)	(0.14)	(0.15)	(0.06)	(0.05)	(0.08)
R^2	0.69	0.58	0.65	0.68	0.77	0.65
Num. obs.	158	158	158	158	158	158
F statistic	16.87	10.88	14.23	16.33	25.84	14.39

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized change in employment-to-population ratio in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Coefficients represent the percentage point change in the sectoral employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Control variables include the log of the population in 1980, the change in robot, the change in the emp-to-pop in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table C.6: OLS Estimates of the Sectoral Wage Impact of ICT and SDB during Digital Technology Phases

	OLS Reg. – Dep. var.: Annualized Δ Average wage (in log) $\times$ 100					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] *Agriculture*						
ICT Exposure	0.58	−3.19	0.84	3.84*	−1.56	−1.27
	(0.52)	(2.43)	(2.39)	(2.05)	(1.93)	(1.52)
SDB Exposure	−1.09	−0.25	3.22	0.15	−1.45*	−0.62
	(1.02)	(3.31)	(2.44)	(2.49)	(0.75)	(1.39)
R^2	0.68	0.51	0.55	0.54	0.54	0.58
Num. obs.	153	154	154	153	153	153
F statistic	16.68	8.42	9.68	9.35	9.44	11.12
[B] *Industry*						
ICT Exposure	−0.13	0.10	0.28	−1.07	0.34	−0.53
	(0.18)	(0.45)	(0.41)	(0.70)	(0.65)	(0.34)
SDB Exposure	−0.07	−0.52	−0.35	1.53**	−1.23***	−0.33
	(0.40)	(0.70)	(0.50)	(0.64)	(0.30)	(0.31)
R^2	0.68	0.64	0.70	0.53	0.76	0.63
Num. obs.	155	155	155	155	155	155
F statistic	17.20	14.13	18.86	9.00	25.77	13.57
[C] *Services*						
ICT Exposure	−0.17	−0.02	0.09	0.07	0.14	0.44
	(0.16)	(0.37)	(0.19)	(0.57)	(0.47)	(0.42)
SDB Exposure	0.13	−0.53	0.46	0.06	0.07	0.77*
	(0.33)	(0.44)	(0.30)	(0.33)	(0.14)	(0.45)
R^2	0.71	0.68	0.73	0.38	0.86	0.60
Num. obs.	155	155	155	155	155	155
F statistic	20.16	16.83	22.29	4.96	51.51	12.21

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the OLS regressions where the outcome variable is the annualized log-change in average wage in Agriculture (Panel A), Industry (Panel B) and Services (Panel C) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Coefficients can be interpreted as the percentage change in the sectoral average wage to a one-standard-deviation increase in exposure to the technology during the cycle phase. Control variables include the log of the population in 1980, the change in robot, the change in the average wage in 1980-1994 to account for pre-trends, final demand and trade exposure respectively over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

C.2 First Stage IV Regressions

Tables C.7, C.8, and C.9 summarize the estimation of the first-stage IV regressions, for all technology cycle phases, for robots, digital technologies, ICT, and SDB, respectively.

Table C.7: First-Stage Regression Robot Breakthroughs (Robots)

	First Stage IV Regression – Dep. var.: ROB Exposure				
	All	Robotics			Intelligent Robots
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
Intercept	-1.30^{**}	-0.55^{***}	-0.27^{***}	-0.33	-0.14
	(0.56)	(0.15)	(0.09)	(0.24)	(0.12)
ROB Exposure (US)	1.71^{***}	3.08^{***}	1.53^{***}	1.11^{**}	1.24^{***}
	(0.34)	(0.37)	(0.20)	(0.51)	(0.33)
R^2	0.52	0.62	0.61	0.18	0.36
Num. obs.	158	158	158	158	158
F statistic	165.70	257.96	242.33	34.95	85.94

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for robots (ROB). The dependent variables represent the robot exposure of European regions in shift-share. Robot Exposure (US) is the instrument variable also constructed as a shift-share with the change in US stock per thousand workers. Regressions are weighted by the population in 1980.

Table C.8: First-Stage Regression Digital Technologies Breakthroughs (ICT)

	First Stage IV Regression – Dep. var.: ICT Exposure					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
Intercept	-0.25	0.24	0.05	0.02	-0.28	-0.15
	(0.31)	(0.17)	(0.05)	(0.16)	(0.27)	(0.09)
ICT Exposure (US)	0.21^{***}	0.29^{**}	0.16^{**}	0.20^{**}	0.16	0.18^{***}
	(0.03)	(0.12)	(0.07)	(0.10)	(0.10)	(0.04)
R^2	0.24	0.09	0.07	0.06	0.04	0.14
Num. obs.	158	158	158	158	158	158
F statistic	49.57	14.56	11.34	10.79	6.35	24.51

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for information and communication technology (ICT). The dependent variables represent the ICT exposure of European regions in shift-share. ICT Exposure (US) is the instrument variable, also constructed as a shift-share with the change in US stock per thousand workers. Regressions are weighted by the population in 1980.

Table C.9: First-Stage Regression Digital Technologies Breakthroughs (Software & Database)

	First Stage IV Regression – Dep. var.: SDB Exposure					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
Intercept	-0.39	0.17	0.11	-0.22	-0.23	-0.16
	(0.53)	(0.16)	(0.11)	(0.14)	(0.14)	(0.11)
SDB Exposure (US)	0.55^{***}	0.48^{***}	0.36^{**}	0.71^{***}	0.44^{***}	0.70^{***}
	(0.10)	(0.12)	(0.16)	(0.13)	(0.09)	(0.12)
R^2	0.28	0.16	0.07	0.29	0.20	0.36
Num. obs.	158	158	158	158	158	158
F statistic	59.46	30.82	12.65	63.20	39.61	89.40

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the first stage of the IV regressions for software and database (SDB). The dependent variables represent the SDB exposure of European regions in shift-share. SDB Exposure (US) is the instrument variable, also constructed as a shift-share with the change in US stock per thousand workers. Regressions are weighted by the population in 1980.

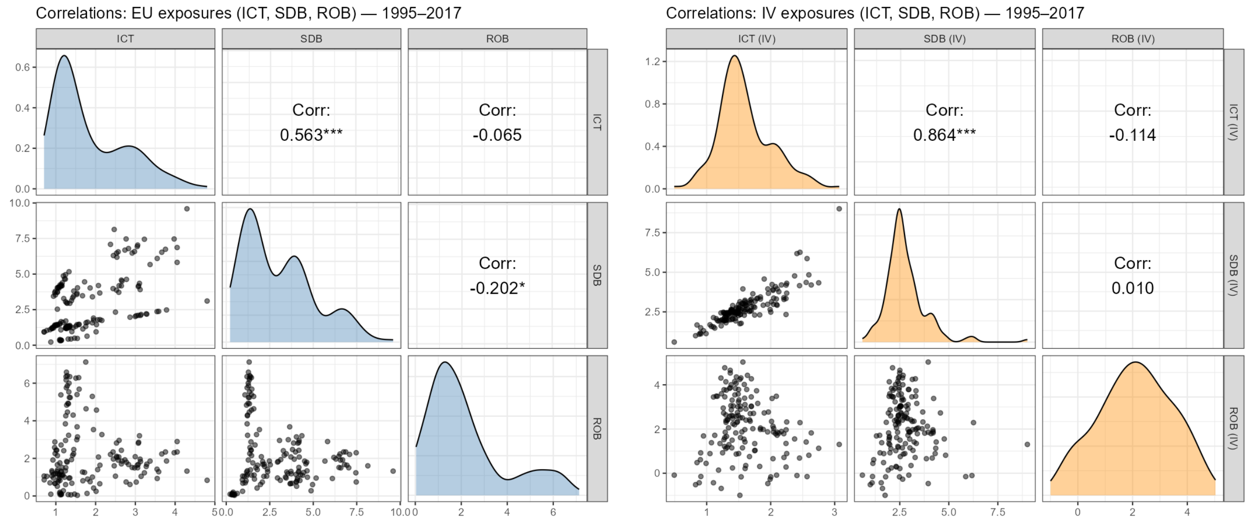
C.3 Second Stage IV Regressions

D Validity and Robustness Checks

D.1 Digital Technologies: ICT versus SDB

Figure D.1 reports the pairwise correlations among the standardized regional exposures to ICT, SDB, and robots (ROB), and among the corresponding instruments. Tables D.1 and D.2 report the Sanderson–Windmeijer weak-identification diagnostics for the joint ICT+SDB specification and for the combined DIG specification, respectively. Tables D.3, D.4, and D.5 report the estimates obtained when the two digital technologies are combined into a single measure ($DIG = ICT + SDB$) and when each is entered on its own.

Figure D.1: Correlations among Digital and Robot Exposures (1995–2017)



(a) Regional exposures

(b) Instruments (US shocks)

Notes: Each panel reports the pairwise Pearson correlations (upper triangle), kernel densities (diagonal), and scatter plots (lower triangle) of the standardized exposures to information and communication technology (ICT), software and databases (SDB), and robots (ROB) over 1995–2017. Panel (a) uses the European (endogenous) exposures; panel (b) uses the instruments constructed from US sectoral technology investment. ICT and SDB exposures are positively but moderately correlated (0.56 for the exposures, 0.86 for the instruments), whereas both are essentially uncorrelated with robot exposure. Stars denote the significance of the correlation coefficient ($^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$).

Table D.1: Weak-Identification Diagnostics: ICT and SDB Entered Jointly (1995–2017)

Diagnostic test	Δ Emp-to-pop ($\times 100$)	Δ Log Wage ($\times 100$)
SW F-stat: ROB	29.07 [0.000]	28.85 [0.000]
SW F-stat: ICT	35.40 [0.000]	38.03 [0.000]
SW F-stat: SDB	37.72 [0.000]	38.55 [0.000]
Wu–Hausman	1.32 [0.272]	2.52 [0.061]
Sargan	—	—

Notes: This table reports instrumental-variable diagnostics for the long-difference (1995–2017) specification in which robots (ROB), ICT, and SDB exposures are entered jointly and instrumented by their US counterparts. The Sanderson–Windmeijer (SW) F-statistic is the conditional first-stage F for each endogenous regressor, testing whether it is separately identified given the other instrumented regressors (p-values in brackets). All SW statistics comfortably exceed conventional weak-instrument thresholds, indicating that each technology is strongly and separately identified even when the three exposures enter together. Wu–Hausman reports the test of regressor endogeneity. The Sargan overidentification test is not defined because the model is exactly identified. Regressions are weighted by the population in 1980.

Table D.2: Weak-Identification Diagnostics: Combined Digital Measure (1995–2017)

Diagnostic test	Δ Emp-to-pop ($\times 100$)	Δ Log Wage ($\times 100$)
SW F-stat: ROB	42.03 [0.000]	41.01 [0.000]
SW F-stat: DIG	77.54 [0.000]	78.63 [0.000]
Wu–Hausman	1.87 [0.158]	1.54 [0.217]
Sargan	—	—

Notes: This table reports instrumental-variable diagnostics for the long-difference (1995–2017) specification in which robots (ROB) and the combined digital measure (DIG = ICT + SDB) are entered and instrumented by their US counterparts. The Sanderson–Windmeijer (SW) F-statistic is the conditional first-stage F for each endogenous regressor (p-values in brackets). Wu–Hausman reports the test of regressor endogeneity. The Sargan over-identification test is not defined because the model is exactly identified. Regressions are weighted by the population in 1980.

Table D.3: Impact of the Combined Digital Measure (DIG = ICT + SDB) during Digital Technology Cycles

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
DIG Exposure	0.00	0.04	-0.09	-0.01	-0.02	0.02
	(0.02)	(0.07)	(0.08)	(0.05)	(0.04)	(0.05)
R^2	0.64	0.73	0.70	0.81	0.90	0.83
Num. obs.	158	158	158	158	158	158
F statistic	14.84	21.80	19.13	34.10	73.02	38.91
[B] Δ *Average wage (in log)* $\times$ *100*						
DIG Exposure	-0.00	-0.09	0.38^{***}	0.24	0.04	0.54^{**}
	(0.06)	(0.19)	(0.14)	(0.16)	(0.07)	(0.21)
R^2	0.63	0.59	0.79	0.71	0.89	0.56
Num. obs.	158	158	158	158	158	158
F statistic	13.93	11.99	31.77	19.79	68.38	10.42

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to the combined digital measure (DIG = ICT + SDB) is calculated as a shift-share variable and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.4: Impact of ICT during Digital Technology Cycles (ICT Entered Alone)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
ICT Exposure	0.01	0.07^{*}	-0.16^{*}	-0.01	-0.05^{**}	-0.01
	(0.01)	(0.04)	(0.08)	(0.04)	(0.03)	(0.04)
R^2	0.64	0.73	0.70	0.81	0.90	0.82
Num. obs.	158	158	158	158	158	158
F statistic	14.87	22.34	19.48	34.06	75.25	38.80
[B] Δ *Average wage (in log)* $\times$ *100*						
ICT Exposure	-0.05	-0.20	0.47^{**}	0.22^{*}	0.03	0.43^{***}
	(0.05)	(0.13)	(0.19)	(0.11)	(0.06)	(0.12)
R^2	0.63	0.60	0.79	0.70	0.89	0.54
Num. obs.	158	158	158	158	158	158
F statistic	14.12	12.24	31.78	19.59	68.30	9.85

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases, with information and communication technology (ICT) entered as the only digital regressor (SDB excluded). The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to ICT is calculated as a shift-share variable and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.5: Impact of SDB during Digital Technology Cycles (SDB Entered Alone)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
SDB Exposure	-0.01	0.01	-0.06	-0.02	0.02	0.03
	(0.01)	(0.03)	(0.06)	(0.03)	(0.02)	(0.03)
R^2	0.64	0.72	0.70	0.81	0.90	0.83
Num. obs.	158	158	158	158	158	158
F statistic	14.87	21.58	18.97	34.12	73.11	39.25
[B] Δ *Average wage (in log)* × *100*						
SDB Exposure	0.07	-0.01	0.32^{**}	0.20^{**}	0.04	0.28^{***}
	(0.06)	(0.12)	(0.14)	(0.10)	(0.06)	(0.09)
R^2	0.63	0.59	0.79	0.70	0.89	0.53
Num. obs.	158	158	158	158	158	158
F statistic	14.15	11.91	31.65	19.68	68.38	9.34

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases, with software and databases (SDB) entered as the only digital regressor (ICT excluded). The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposure to SDB is calculated as a shift-share variable and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

D.2 Rotemberg Weights

Our identification strategy relies on a shift–share (Bartik) instrumental variable, which combines pre-determined regional exposure shares (sectoral employment in 1980), and aggregate technology shocks (US technology investment by sector and phase). Recent methodological advances have shown that Bartik IVs require additional scrutiny beyond standard first-stage strength (Goldsmith-Pinkham et al. 2020). The key concern is that identification in Bartik IVs may be driven by a weighted average of many sector-time shocks, where the weights in our case depend on the pre-determined regional industrial structure. As a result, the estimated coefficient may be implicitly dominated by a small subset of shocks or regions, potentially undermining the quasi-experimental interpretation.

We follow Goldsmith-Pinkham et al. (2020) to assess whether our instrument satisfies two conditions related to the contribution of each instrument to the overall estimate. First, we examine whether the estimated effects are driven by a small number of highly influential components. Second, we test whether results are sensitive to excluding regions with the highest Rotemberg weights. Their approach decomposes the IV estimator into Rotemberg weights (α_k) and the associated just-identified estimators (β_k), thereby making explicit how each instrument loads onto the aggregate coefficient. This decomposition is informative for validity: if an instrument is misspecified, its Rotemberg weight captures the extent to which such misspecification would contaminate the IV estimate. Consequently, when α_k is small, any bias specific to the k^{th} instrument exerts limited influence on the overall estimate. This diagnostic provides a transparent assessment of whether the results are driven by a small number of instruments or are stable across the full set of identifying shocks.

In light of this diagnostic, Tables D.6, D.7, and D.8 in the appendix report summary statistics of the Rotemberg weights for robots, ICT, and SDB, respectively. For each technology, we list the five country–industry combinations that contribute the most to the identifying variation.

Robots. For robots, the top five country–industry pairs account for 92.25% of the total absolute Rotemberg weight. As expected, the identifying variation is concentrated in manufacturing, the dominant adopter of industrial robots in the IFR data (Müller 2022). The weights reveal a particularly strong influence of Germany, which alone contributes nearly 64% of the total.

Figure D.2 further illustrates the relationship between Rotemberg weights (α_k) and the just-identified estimators (β_k). Marker size reflects the magnitude of α_k, and colors distinguish positive and negative weights. The German manufacturing instrument yields an estimate close to the overall IV coefficient, mitigating concerns that its large weight could have pulled a different underlying relationship. Some heterogeneity arises among low-weight instruments, which have limited power to distort the average estimate.

To assess whether the concentration of weights in Germany biases our results, we re-estimate the IV models excluding all German regions. As shown in Table D.9, the resulting coefficients closely match those in Table 2, indicating that the dominance of German instruments does not affect the IV estimates. This robustness confirms that the positive employment effects of robots are not an artifact of Germany's specific economy but a broader European phenomenon.

Information and Communication Technology (ICT). For ICT exposure, the top five country–industry pairs account for 43.37% of the total absolute weight. The most recurrent contributor is sector G–J, which encompasses information and communication activities. These sectors play a central role in both the use and production of ICT technologies, giving them a prominent place in the instrument's variation.

Figure D.3 plots the just-identified estimates against their Rotemberg weights. A limited set of instruments receives relatively large weights, and the associated β_k values cluster tightly around the overall IV estimate (shown by the dashed line). Even among the instruments with negative weights, the corresponding estimates remain close to the aggregate coefficient, which reduces concerns about instability in the underlying first-stage relationships.[29]

Given that Spanish regions in sectors O–U and G–J emerge as influential units, we conduct a robustness check excluding these regions. Table D.10 shows that the resulting coefficients remain very similar to those in Table 3, reinforcing the conclusion that the IV estimates are not driven by a narrow subset of influential Spanish instruments.

Software and Database (SDB). For SDB exposure, the top five industries account for 55.57% of the total absolute Rotemberg weight. As for ICT, this includes sector J—an important producer of software and digital content—but also sector K–N, which encompasses financial and business services. The latter's prominence aligns with the sector's heavy reliance on software and database technologies.

Figure D.4 shows that the instruments with the largest weights produce just-identified estimates that lie close to the aggregate IV coefficient, while the observed heterogeneity stems primarily from instruments receiving much smaller weights. Consequently, the scope for such heterogeneity to bias the overall estimate is limited.

Because French regions in sectors K–N and G–J account for a non-trivial share of the identifying variation, we re-estimate the models excluding these regions. Table D.11 demonstrates that the results remain closely aligned with the baseline estimates in Table 3, providing further reassurance that the IV estimates are robust to influential SDB instruments.

Taken together, the Rotemberg weights provide three forms of evidence that strengthen the credibility of our identification strategy. First, they show that the instruments with the largest weights produce just-identified estimates that are tightly clustered around the aggregate IV coefficient. This pattern is what would be expected if the underlying shift–share structure is valid: the main sources of identifying variation deliver internally consistent estimates rather than outliers that dominate the results.

Second, although some instruments carry large weights—as is common in Bartik settings—they do not drive the results. When we remove the countries associated with the most influ-

[29] Negative weights are inherent to the Bartik decomposition and do not by themselves imply misspecification; what matters is whether the associated just-identified estimates diverge substantively from the aggregate coefficient.

ential instruments (e.g., German manufacturing for robots, Spanish G–J for ICT, French K–N for SDB), the estimated coefficients remain remarkably stable. This stability rules out the possibility that the IV results are an artifact of a single country–industry shock or an idiosyncratic pattern in a dominant sector.

Finally, the heterogeneity across low-weight instruments—while present—is economically negligible for the validity of the IV. By construction, differences in β_k for instruments assigned near-zero weights cannot meaningfully bias the aggregate estimate. This is especially important in our setting, where measurement error or idiosyncratic innovations in small country–industry cells could otherwise raise concerns about overfitting or weak-signal bias in Bartik instruments.

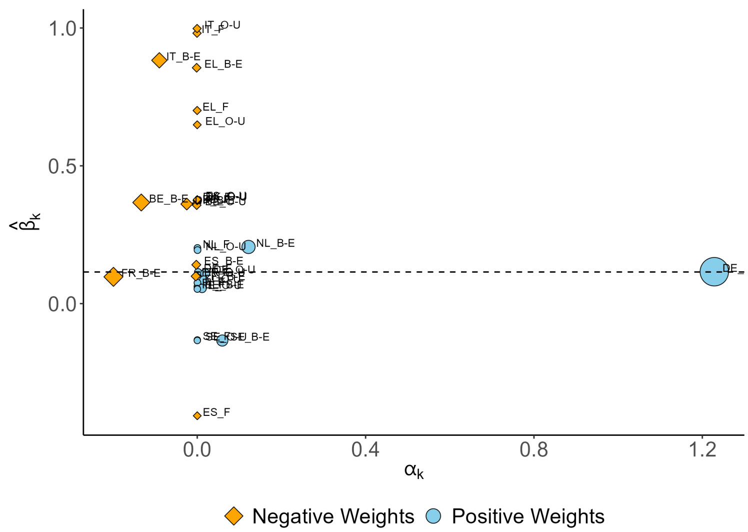
Tables D.6, D.7, and D.8 summarize the Rotemberg weights for Robots, ICT, and SDB, respectively. Figures D.2, D.3, and D.4 show the heterogeneity in Rotemberg weights for Robots, ICT, and SDB, respectively.

Table D.6: Summary of Rotemberg Weights for Robots

Country	NACE	g_k	α_k	β_k	Share (in %)
DE	B-E	16.093	1.229	0.116	63.950
FR	B-E	4.246	-0.199	0.097	10.364
BE	B-E	5.551	-0.133	0.367	6.923
NL	B-E	8.830	0.122	0.206	6.340
IT	B-E	6.789	-0.090	0.883	4.688

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

Figure D.2: Heterogeneity in β_k for Robots



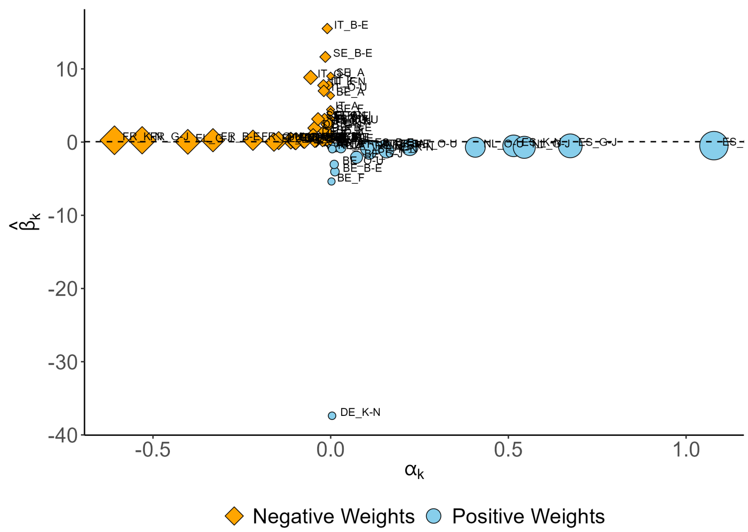
Notes: This figure plots the relationship between each instrument and the Rotemberg weights for robots. Each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table 2.

Table D.7: Summary of Rotemberg Weights for ICT

Country	NACE	g_k	α_k	β_k	Share (in %)
ES	O-U	3.377	1.078	-0.484	13.609
ES	G-J	1.868	0.674	-0.512	8.508
FR	K-N	3.854	-0.608	0.251	7.679
NL	G-J	3.780	0.545	-0.715	6.875
FR	G-J	1.573	-0.531	0.250	6.696

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

Figure D.3: Heterogeneity in β_k for ICT



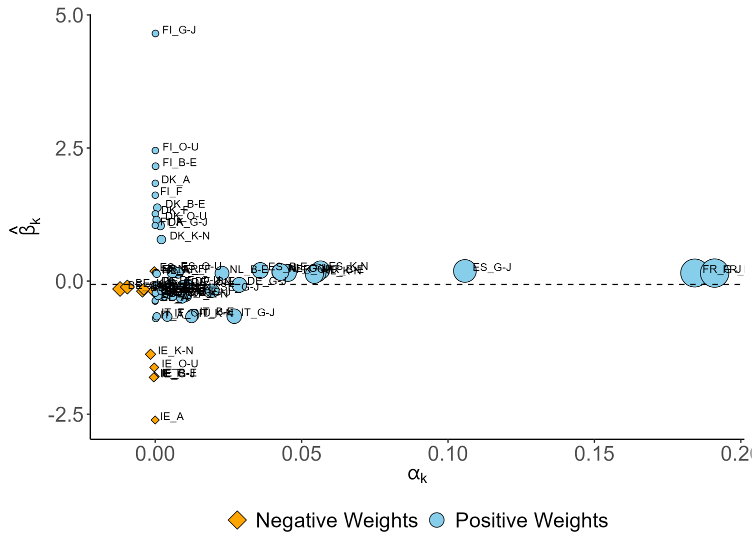
Notes: This figure plots the relationship between each instrument and the Rotemberg weights for information and communication technologies, where each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights, while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table 3.

Table D.8: Summary of Rotemberg Weights for SDB

Country	NACE	g_k	α_k	β_k	Share (in %)
FR	K-N	16.104	0.191	0.150	17.901
FR	G-J	7.337	0.184	0.152	17.264
ES	G-J	7.879	0.106	0.191	9.910
ES	K-N	13.479	0.056	0.207	5.289
FR	B-E	2.225	0.055	0.151	5.173

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

Figure D.4: Heterogeneity in β_k for SDB



Notes: This figure plots the relationship between each instrument and the Rotemberg weights for software and database. Each point corresponds to a separate instrument's estimate (industry share). The y-axis shows the estimated β_k for each instrument, while the x-axis displays the Rotemberg weights α_k estimated by applying the methodology developed by Goldsmith-Pinkham et al. (2020). The scatter points are weighted by the Rotemberg weights, while the colors reflect their sign (positive and negative). The horizontal dashed line represents the value of the overall IV β displayed in the first column of Table 3.

Table D.9 shows the labor market impacts of robots, excluding observations from Germany. Tables D.10 and D.11 show the labor market impacts of ICT and SDB separately, excluding observations from Spain and France, respectively.

Table D.9: Impact of Robots during Robot Phases Excluding Germany

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.08^{*}	0.14	0.03	0.00	0.07^{*}
	(0.04)	(0.08)	(0.04)	(0.10)	(0.03)
R^2	0.59	0.78	0.89	0.71	0.85
Num. obs.	128	128	128	128	128
F statistic	9.42	23.08	50.72	15.92	35.49
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	-0.09	-0.12	0.19	-0.21	0.32^{***}
	(0.16)	(0.24)	(0.12)	(0.28)	(0.11)
R^2	0.69	0.63	0.87	0.76	0.47
Num. obs.	128	128	128	128	128
F statistic	14.11	11.13	44.02	20.75	5.82

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980. The sample excludes German NUTS-2 regions.

Table D.10: Impact of ICT and SDB during Digital Technologies Cycles Excluding Spain

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.03	0.36^{**}	-0.39^{*}	0.06	-0.10^{**}	-0.00
	(0.03)	(0.14)	(0.20)	(0.05)	(0.04)	(0.04)
SDB Exposure	-0.03^{*}	-0.33^{**}	0.21	-0.06	0.07^{*}	0.03
	(0.02)	(0.14)	(0.14)	(0.05)	(0.04)	(0.04)
R^2	0.69	0.58	0.52	0.79	0.87	0.65
Num. obs.	139	139	139	139	139	139
F statistic	15.54	9.86	7.76	26.92	48.65	13.24
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.19^{**}	-1.08^{***}	0.42	0.10	0.03	0.39^{*}
	(0.08)	(0.40)	(0.51)	(0.19)	(0.11)	(0.23)
SDB Exposure	0.18^{***}	1.04^{***}	0.09	0.11	-0.00	0.23^{**}
	(0.07)	(0.29)	(0.33)	(0.20)	(0.10)	(0.10)
R^2	0.68	0.65	0.76	0.51	0.90	0.59
Num. obs.	139	139	139	139	139	139
F statistic	15.22	13.43	22.28	7.43	61.31	10.05

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980. The sample excludes Spanish NUTS-2 regions.

Table D.11: Impact of ICT and SDB during Digital Technologies Cycles Excluding France

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.02	0.36^{**}	-0.32^{*}	-0.01	-0.13^{***}	-0.02
	(0.02)	(0.15)	(0.18)	(0.06)	(0.04)	(0.05)
SDB Exposure	-0.02	-0.28^{*}	0.14	-0.01	0.08^{**}	0.03
	(0.02)	(0.14)	(0.13)	(0.05)	(0.04)	(0.03)
R^2	0.60	0.76	0.69	0.81	0.92	0.81
Num. obs.	136	136	136	136	136	136
F statistic	10.46	21.44	15.68	29.78	80.39	30.06
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.26^{***}	-1.16^{***}	0.15	0.01	0.06	0.05
	(0.06)	(0.30)	(0.45)	(0.18)	(0.12)	(0.16)
SDB Exposure	0.26^{***}	0.92^{***}	0.16	0.19	-0.00	0.16^{**}
	(0.06)	(0.24)	(0.30)	(0.19)	(0.09)	(0.07)
R^2	0.76	0.76	0.81	0.77	0.89	0.65
Num. obs.	136	136	136	136	136	136
F statistic	21.97	22.40	28.91	23.42	58.95	12.96

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980. The sample excludes French NUTS-2 regions.

D.3 Pre-Trends

Table D.12 presents the long-difference estimate in the pre-period (1980–1994) in Column (1), the equivalent estimates for the period of analysis (1995–2017) in Column (2), and the corresponding estimates once we control for the pre-period change in the outcome variable in Column (3).

Tables D.13 and D.14 show the labor market impacts of digital technologies (ICT and SDB) and robots without controlling for the change in the outcome variable in the pre-period (1980–1994).

Table D.12: Pre-Trends in the Impact of Automation Technologies (Long-Difference)

	IV Reg. - Δ Employment-to-population $\times$ 100		
	1980-1994	1995-2017	1995-2017 (2)
[A] Δ *Employment-to-population* $\times$ *100*			
ROB Exposure	0.00	0.02^{**}	0.02^{*}
	(0.02)	(0.01)	(0.01)
ICT Exposure	0.11^{***}	0.04	0.02
	(0.04)	(0.03)	(0.03)
SDB Exposure	-0.05	-0.03	-0.02
	(0.05)	(0.03)	(0.02)
R^2	0.62	0.57	0.63
Num. obs.	158	158	158
F statistic	15.43	12.72	15.27
[B] Δ *Average wage (in log)* $\times$ *100*			
ROB Exposure	-0.10^{**}	-0.04	-0.04
	(0.04)	(0.04)	(0.05)
ICT Exposure	-0.20^{*}	-0.22^{***}	-0.22^{***}
	(0.10)	(0.08)	(0.07)
SDB Exposure	0.30^{***}	0.20^{***}	0.20^{***}
	(0.09)	(0.06)	(0.06)
Pre-period Change			✓
R^2	0.48	0.65	0.65
Num. obs.	158	158	158
F statistic	8.90	17.53	16.33

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and in the logarithm of the average wage (Panel B). The first column reports the coefficients for the period 1980–1994 (Pre-trend) and the second column for 1995-2017. Control variables include the log of the population in 1980 and country fixed effects. Regressions are weighted by the population in 1980.

Table D.13: Impact of ICT and SDB during Digital Technologies Cycles Without Controlling for the Pre-Trend

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.05^{**}	0.52^{**}	-0.37^{**}	-0.01	-0.10^{**}	-0.00
	(0.02)	(0.20)	(0.17)	(0.06)	(0.04)	(0.04)
SDB Exposure	-0.06^{***}	-0.37^{*}	0.19	0.00	0.07^{*}	0.02
	(0.02)	(0.19)	(0.12)	(0.05)	(0.04)	(0.03)
R^2	0.61	0.70	0.71	0.80	0.91	0.81
Num. obs.	158	158	158	158	158	158
F statistic	13.00	19.38	19.76	33.21	79.12	34.20
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.23^{***}	-1.17^{***}	0.25	0.10	0.02	0.37^{*}
	(0.08)	(0.37)	(0.46)	(0.19)	(0.12)	(0.21)
SDB Exposure	0.26^{***}	0.98^{***}	0.20	0.15	0.02	0.19^{**}
	(0.07)	(0.27)	(0.30)	(0.18)	(0.10)	(0.09)
R^2	0.66	0.63	0.79	0.71	0.89	0.56
Num. obs.	158	158	158	158	158	158
F statistic	15.71	13.94	30.65	19.70	68.26	10.37

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects.

Table D.14: Impact of Robots during Robot Phases Without Controlling for the Pre-Trend

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.11^{**}	0.22^{*}	0.02	-0.00	0.05
	(0.05)	(0.11)	(0.04)	(0.09)	(0.04)
R^2	0.61	0.70	0.94	0.71	0.81
Num. obs.	158	158	158	158	158
F statistic	13.00	19.38	125.82	20.27	34.20
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	0.00	-0.12	0.25^{**}	-0.11	0.32^{***}
	(0.13)	(0.22)	(0.11)	(0.26)	(0.12)
R^2	0.66	0.63	0.85	0.77	0.56
Num. obs.	158	158	158	158	158
F statistic	15.71	13.94	45.52	27.51	10.37

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

D.4 Trade Checks

Trade with Eastern European Countries. Chinese import competition was not the only trade shock to affect Western European labor markets over our sample period: integration with Eastern Europe reshaped both import competition and export opportunities (Dauth et al., 2014). We therefore augment the baseline with regional shift–share measures of bilateral trade with ten Eastern European economies—both imports from and exports to the region—constructed per 1980 worker, exactly as for the Chinese import control. Tables D.15 and D.16 add these controls to the robot and digital-technology specifications. The estimates are essentially unchanged: the long-run positive employment effect of robots (0.09, $p < 0.05$) and the opposing long-run wage effects of ICT (-0.24, $p < 0.01$) and SDB ($+0.26$, $p < 0.01$) are indistinguishable from the baseline in sign, magnitude, and significance. Controlling for Eastern European trade does not affect our results.

Imports from the US. A distinct concern is a direct-competition channel whereby US technology adoption raises US productivity and erodes the market share of European competitors—a channel a China-based trade control would not capture. Rather than replace the Chinese import control—the canonical measure of import competition (Autor et al., 2013)—we add a regional shift–share measure of imports from the US, built per 1980 worker exactly as for the Chinese control, alongside it. Tables D.17 and D.18 report the results. The estimates are again essentially unchanged from the baseline: the long-run employment effect of robots (0.10, $p < 0.05$) and the opposing long-run wage effects of ICT (-0.23, $p < 0.01$) and SDB ($+0.26$, $p < 0.01$) retain their sign, magnitude, and significance. Adding a US import control does not affect our results.

Table D.15: IV Estimates of the Labor Market Impact of Robots during Robot Phases (adding trade exposure from Eastern Europe)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.09^{**}	0.13	0.03	-0.02	0.06^{*}
	(0.04)	(0.09)	(0.05)	(0.12)	(0.03)
R^2	0.65	0.76	0.94	0.71	0.83
Num. obs.	158	158	158	158	158
F statistic	13.36	22.63	113.66	17.98	34.95
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	-0.01	-0.04	0.25^{**}	-0.09	0.35^{***}
	(0.14)	(0.26)	(0.12)	(0.35)	(0.12)
R^2	0.66	0.63	0.85	0.78	0.57
Num. obs.	158	158	158	158	158
F statistic	13.89	12.36	40.24	25.32	9.55

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the robot technology adoption life phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and from Eastern European countries, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.16: IV Estimates of the Labor Market Impact of ICT and SDB during Digital Technology Phases (adding trade exposure from Eastern Europe)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.03	0.35^{**}	-0.39^{**}	0.00	-0.10^{**}	-0.01
	(0.02)	(0.14)	(0.18)	(0.09)	(0.04)	(0.04)
SDB Exposure	-0.03^{*}	-0.27^{*}	0.18	-0.02	0.07^{*}	0.03
	(0.02)	(0.14)	(0.13)	(0.05)	(0.04)	(0.03)
R^2	0.65	0.76	0.71	0.81	0.91	0.83
Num. obs.	158	158	158	158	158	158
F statistic	13.36	22.63	17.56	30.12	69.93	34.95
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.22^{***}	-1.18^{***}	0.29	0.02	0.01	0.39^{*}
	(0.08)	(0.37)	(0.47)	(0.21)	(0.11)	(0.21)
SDB Exposure	0.26^{***}	1.00^{***}	0.13	0.16	0.03	0.19^{**}
	(0.07)	(0.27)	(0.30)	(0.19)	(0.10)	(0.08)
R^2	0.66	0.63	0.79	0.71	0.89	0.57
Num. obs.	158	158	158	158	158	158
F statistic	13.89	12.36	28.14	17.59	60.32	9.55

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and from Eastern European countries, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.17: IV Estimates of the Labor Market Impact of Robots during Robot Phases (adding trade exposure from U.S.)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.09^{**}	0.21^{**}	0.03	-0.03	0.07^{*}
	(0.04)	(0.09)	(0.04)	(0.10)	(0.04)
R^2	0.65	0.76	0.94	0.71	0.83
Num. obs.	158	158	158	158	158
F statistic	13.38	22.89	113.71	18.22	34.87
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	0.02	-0.12	0.25^{**}	-0.13	0.35^{**}
	(0.14)	(0.24)	(0.11)	(0.27)	(0.14)
R^2	0.66	0.63	0.85	0.78	0.56
Num. obs.	158	158	158	158	158
F statistic	13.88	12.31	40.19	25.32	9.29

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the robot technology adoption life phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and from the U.S., respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.18: IV Estimates of the Labor Market Impact of ICT and SDB during Digital Technology Phases (adding trade exposure from U.S.)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
ICT Exposure	0.03	0.33^{**}	-0.53^{**}	0.02	-0.12^{***}	-0.01
	(0.02)	(0.13)	(0.21)	(0.06)	(0.05)	(0.04)
SDB Exposure	-0.03	-0.20	0.22^{*}	0.01	0.08^{*}	0.05
	(0.02)	(0.14)	(0.13)	(0.06)	(0.04)	(0.04)
R^2	0.65	0.76	0.71	0.81	0.91	0.83
Num. obs.	158	158	158	158	158	158
F statistic	13.38	22.89	18.06	30.51	70.51	34.87
[B] Δ *Average wage (in log)* $\times$ *100*						
ICT Exposure	-0.23^{***}	-1.19^{***}	0.48	0.09	0.08	0.39^{*}
	(0.08)	(0.35)	(0.51)	(0.20)	(0.14)	(0.22)
SDB Exposure	0.25^{***}	1.01^{***}	0.06	0.06	-0.01	0.24^{**}
	(0.09)	(0.33)	(0.30)	(0.23)	(0.12)	(0.10)
R^2	0.66	0.63	0.80	0.71	0.89	0.56
Num. obs.	158	158	158	158	158	158
F statistic	13.88	12.31	28.17	17.65	61.49	9.29

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a 1-SD increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and from the U.S., respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Automation-Induced US Reshoring. A distinct threat to the exclusion restriction is automation-induced reshoring: if US technology investment lowers US production costs and leads US firms to substitute domestic production for imports previously sourced from Europe, our instrument could affect European labor markets directly through trade, rather than only through European technology adoption. We probe this channel in two ways. First, Tables D.19, D.20, and D.21 re-estimate the three main specifications after dropping the quartile of regions most dependent on the US export market in 1995, where the reshoring channel should be strongest. Second, Tables D.22, D.23, and D.24 augment the baseline with regional shift–share measures of bilateral trade exposure to the United States—both exports to and imports from the US—built analogously to the Chinese-import control.

Across both exercises the estimates preserve the sign and phase pattern of the baseline. Adding the US-trade controls leaves the estimates almost unchanged: in particular, the opposing long-run wage effects of ICT (-0.23) and SDB ($+0.26$) and the positive long-run employment effect of robots are essentially identical to the baseline in Tables 3 and 2. Excluding the most US-export-dependent regions preserves the same signs throughout; the robot employment effect is, if anything, stronger, while the ICT/SDB long-run wage contrast retains its signs but loses precision, as expected given the smaller sample (118 rather than 158 regions). We find no evidence that automation-induced US reshoring drives the baseline results.

Table D.19: Impact of Robots during Robot Phases (Excluding the Most US-Export-Dependent Regions)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.14^{***}	0.12	0.01	0.05	0.08^{*}
	(0.04)	(0.09)	(0.06)	(0.10)	(0.04)
R^2	0.66	0.82	0.94	0.76	0.86
Num. obs.	118	118	118	118	118
F statistic	11.19	26.07	98.74	18.13	37.52
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	0.16	0.35	0.37	0.02	0.54^{***}
	(0.15)	(0.47)	(0.23)	(0.23)	(0.16)
R^2	0.58	0.61	0.88	0.75	0.53
Num. obs.	118	118	118	118	118
F statistic	8.20	9.38	41.34	17.43	6.75

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline robot IV regressions (Table 2) after excluding the top quartile of regions by initial (1995) dependence on the US export market. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the robot technology adoption life phases. The first column is the long-difference estimate for the entire period (1995–2017); the second, third, and fourth columns correspond to the phases of the Robotics cycle; the last column shows the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.20: Impact of ICT and SDB during Digital Technology Phases (Excluding the Most US-Export-Dependent Regions)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.02	0.04	-0.42^{*}	0.03	0.00	-0.01
	(0.03)	(0.12)	(0.23)	(0.09)	(0.06)	(0.05)
SDB Exposure	-0.01	0.12	0.08	-0.06	-0.01	0.06
	(0.04)	(0.13)	(0.18)	(0.12)	(0.06)	(0.06)
R^2	0.66	0.82	0.72	0.78	0.92	0.86
Num. obs.	118	118	118	118	118	118
F statistic	11.19	26.07	15.09	21.08	65.34	37.52
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.19	-0.58	0.19	0.05	-0.12	0.54^{**}
	(0.18)	(0.55)	(0.60)	(0.27)	(0.16)	(0.21)
SDB Exposure	0.25	0.35	0.47	0.56^{*}	0.14	0.31
	(0.23)	(0.47)	(0.40)	(0.32)	(0.16)	(0.20)
R^2	0.58	0.61	0.79	0.70	0.91	0.53
Num. obs.	118	118	118	118	118	118
F statistic	8.20	9.38	22.23	13.91	63.16	6.75

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline ICT/SDB IV regressions (Table 3) after excluding the top quartile of regions by initial (1995) dependence on the US export market. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017); the second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.21: Impact of Digital Technologies (DIG) during Digital Technology Phases (Excluding the Most US-Export-Dependent Regions)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
DIG Exposure	0.02	0.16^{**}	-0.27^{**}	-0.02	-0.01	0.03
	(0.02)	(0.06)	(0.13)	(0.08)	(0.04)	(0.06)
R^2	0.65	0.82	0.71	0.78	0.92	0.86
Num. obs.	118	118	118	118	118	118
F statistic	11.97	27.94	15.78	22.53	70.08	39.84
[B] Δ *Average wage (in log)* $\times$ *100*						
DIG Exposure	-0.02	-0.24	0.67^{**}	0.52^{**}	0.00	0.83^{***}
	(0.06)	(0.26)	(0.27)	(0.25)	(0.08)	(0.29)
R^2	0.57	0.61	0.79	0.70	0.91	0.53
Num. obs.	118	118	118	118	118	118
F statistic	8.45	9.93	23.84	14.63	66.67	7.24

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline combined-digital (DIG = ICT + SDB) IV regressions after excluding the top quartile of regions by initial (1995) dependence on the US export market. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. Columns follow the digital-cycle phases as in Table D.20. Exposure to digital technologies (DIG) is calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.22: Impact of Robots during Robot Phases (Adding US Bilateral Trade Exposure)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* × *100*					
ROB Exposure	0.10^{**}	0.22^{*}	0.03	-0.01	0.06^{**}
	(0.04)	(0.13)	(0.04)	(0.10)	(0.03)
R^2	0.65	0.75	0.94	0.71	0.84
Num. obs.	158	158	158	158	158
F statistic	12.83	20.85	114.24	16.98	35.12
[B] Δ *Average wage (in log)* × *100*					
ROB Exposure	-0.00	-0.26	0.25^{**}	-0.15	0.30^{**}
	(0.13)	(0.35)	(0.11)	(0.24)	(0.12)
R^2	0.66	0.63	0.85	0.78	0.58
Num. obs.	158	158	158	158	158
F statistic	13.14	11.69	38.51	24.16	9.47

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline robot IV regressions (Table 2) adding regional shift–share exposure to US bilateral trade (exports to and imports from the United States) alongside the Chinese-import control. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the robot technology adoption life phases. Columns follow the robot-cycle phases as in Table 2. Exposure to robots (ROB) is calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and bilateral trade exposure to and from the United States, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.23: Impact of ICT and SDB during Digital Technology Phases (Adding US Bilateral Trade Exposure)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
ICT Exposure	0.03	0.36**	−0.38*	0.01	−0.10**	−0.01
	(0.02)	(0.15)	(0.21)	(0.06)	(0.05)	(0.04)
SDB Exposure	−0.03	−0.29*	0.24	−0.00	0.07	0.05
	(0.02)	(0.16)	(0.15)	(0.04)	(0.04)	(0.04)
R^2	0.65	0.75	0.72	0.82	0.91	0.84
Num. obs.	158	158	158	158	158	158
F statistic	12.83	20.85	17.33	30.41	66.59	35.12
[B] Δ *Average wage (in log)* $\times$ *100*						
ICT Exposure	−0.23***	−1.31***	0.19	0.12	−0.02	0.33
	(0.08)	(0.39)	(0.51)	(0.19)	(0.11)	(0.21)
SDB Exposure	0.26***	1.12***	0.29	0.15	0.06	0.17*
	(0.07)	(0.34)	(0.35)	(0.19)	(0.09)	(0.09)
R^2	0.66	0.63	0.80	0.71	0.90	0.58
Num. obs.	158	158	158	158	158	158
F statistic	13.14	11.69	27.07	16.67	58.49	9.47

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline ICT/SDB IV regressions (Table 3) adding regional shift–share exposure to US bilateral trade (exports to and imports from the United States) alongside the Chinese-import control. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. Columns follow the digital-cycle phases as in Table 3. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and bilateral trade exposure to and from the United States, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.24: Impact of Digital Technologies (DIG) during Digital Technology Phases (Adding US Bilateral Trade Exposure)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
DIG Exposure	0.00	0.04	-0.03	0.00	-0.02	0.04
	(0.02)	(0.07)	(0.08)	(0.04)	(0.04)	(0.05)
R^2	0.65	0.73	0.71	0.82	0.90	0.83
Num. obs.	158	158	158	158	158	158
F statistic	13.32	19.71	17.59	32.24	65.63	36.71
[B] Δ *Average wage (in log)* $\times$ *100*						
DIG Exposure	-0.01	-0.13	0.47^{***}	0.26	0.03	0.48^{**}
	(0.06)	(0.21)	(0.18)	(0.16)	(0.07)	(0.21)
R^2	0.63	0.60	0.80	0.71	0.89	0.58
Num. obs.	158	158	158	158	158	158
F statistic	12.31	10.72	28.70	17.67	61.83	10.03

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table replicates the baseline combined-digital (DIG = ICT + SDB) IV regressions adding regional shift–share exposure to US bilateral trade (exports to and imports from the United States) alongside the Chinese-import control. The outcome variable is the annualized change in the employment-to-population ratio (Panel A) and the log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. Columns follow the digital-cycle phases as in Table D.23. Exposure to digital technologies (DIG) is calculated as shift–share variables and then standardized. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure from China and bilateral trade exposure to and from the United States, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

D.5 Breakpoint Sensitivity

Tables D.25 and D.26 show the labor market impacts of robots and digital technologies (ICT and SDB) under alternative cycle phases to show that the results are robust to the period definition of technological cycles.

Table D.25: Impact of Robots during Robot Phases with Alternative Cycle Phases

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable			
	All	Robotics		Intelligent Robots
	(1)	(2)	(3)	(4)
	1995-2017	1995-2000	2000-2010	2010-2017
[A] Δ *Employment-to-population* $\times$ *100*				
ROB Exposure	0.09^{***}	0.28^{***}	0.14	0.03
	(0.03)	(0.07)	(0.10)	(0.02)
R^2	0.65	0.67	0.40	0.82
Num. obs.	158	158	158	158
F statistic	14.20	15.64	5.25	34.48
[B] Δ *Average wage (in log)* $\times$ *100*				
ROB Exposure	0.01	-0.38	-0.21	0.33^{***}
	(0.12)	(0.27)	(0.24)	(0.06)
R^2	0.66	0.43	0.74	0.87
Num. obs.	158	158	158	158
F statistic	14.74	5.91	21.42	53.86

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

Table D.26: Impact of ICT and SDB during Digital Technologies Cycles with Alternative Cycle Phases

	IV Reg. - Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2000	2000-2004	2004-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*						
ICT Exposure	0.03	0.46^{**}	-0.36^{*}	0.01	-0.10^{**}	-0.02
	(0.02)	(0.23)	(0.20)	(0.06)	(0.04)	(0.04)
SDB Exposure	-0.03^{*}	-0.39	0.13	-0.02	0.07^{*}	0.04
	(0.02)	(0.24)	(0.15)	(0.04)	(0.04)	(0.03)
R^2	0.65	0.67	0.72	0.67	0.91	0.83
Num. obs.	158	158	158	158	158	158
F statistic	14.20	15.64	20.03	15.54	74.22	36.88
[B] Δ *Average wage (in log)* $\times$ *100*						
ICT Exposure	-0.23^{***}	-1.53^{**}	-0.11	0.08	0.01	0.36^{*}
	(0.08)	(0.67)	(0.44)	(0.17)	(0.11)	(0.21)
SDB Exposure	0.26^{***}	1.30^{**}	0.30	0.12	0.03	0.20^{**}
	(0.07)	(0.57)	(0.29)	(0.16)	(0.10)	(0.09)
R^2	0.66	0.43	0.81	0.67	0.89	0.56
Num. obs.	158	158	158	158	158	158
F statistic	14.74	5.91	32.19	15.93	64.13	9.78

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication (ICT) and software-database (SDB) are calculated as shift-share variables and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980-1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1980.

D.6 Initial-Year Sensitivity

Our baseline shift–share exposure measures fix regional sectoral employment shares in 1980. This choice is motivated by identification: using shares that predate the main period of analysis by a substantial margin reduces the risk that the exposure measure incorporates early technology adoption, anticipatory restructuring, or other labor-market adjustments that occurred before 1995. At the same time, using a very early base year raises the concern that regional industrial structures may have changed between 1980 and the beginning of the main analysis window.

To assess this trade-off, Tables D.27 and D.28 replicate the main IV specifications using sectoral employment shares fixed in 1990. The results preserve the main qualitative patterns documented in the baseline tables. Robot exposure remains positively associated with employment during the full period and the early phases of the robot life cycle, while the later robot phases display weaker or less precise effects. For digital technologies, the signs and phase-specific interpretation of the ICT and SDB estimates are broadly unchanged, with the expected loss of precision in some phases.

These estimates confirm that the results are not mechanically driven by the 1980 base year. We nevertheless retain 1980 shares in the preferred specification because they are less likely to embed endogenous adjustments associated with the early diffusion of ICT and software-related technologies before the start of the 1995–2017 analysis period.

Table D.27: Impact of Robots during Robot Cycles (1990 Shares)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable				
	All	Robotics			Intelligent Robots
	(1)	(2)	(3)	(4)	(5)
	1995-2017	1995-2002	2002-2007	2007-2014	2014-2017
[A] Δ *Employment-to-population* $\times$ *100*					
ROB Exposure	0.13^{***}	0.29^{***}	0.04	-0.03	0.06^{*}
	(0.03)	(0.07)	(0.04)	(0.06)	(0.03)
R^2	0.61	0.71	0.93	0.73	0.81
Num. obs.	158	158	158	158	158
F statistic	12.99	20.03	117.07	22.01	35.05
[B] Δ *Average wage (in log)* $\times$ *100*					
ROB Exposure	-0.12	-0.11	0.20^{**}	-0.08	0.43^{***}
	(0.12)	(0.26)	(0.09)	(0.18)	(0.10)
R^2	0.63	0.59	0.85	0.77	0.59
Num. obs.	158	158	158	158	158
F statistic	13.92	12.03	47.99	27.11	12.08

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the robot technology adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second, third, and fourth columns correspond to the phases of the Robotics cycle. The last column shows the coefficient for the first phase of the Intelligent Robots cycle. Exposure to robots (ROB) is calculated using shift–share variables based on 1990 sectoral employment shares and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in ICT and SDB, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1990.

Table D.28: Impact of ICT and SDB during Digital Technology Cycles (1990 Shares)

	IV Reg. – Dep. var.: Annualized Δ in Outcome Variable					
	All	Web 1.0		GraphUI - Cloud		Big Data - AI
	(1)	(2)	(3)	(4)	(5)	(6)
	1995-2017	1995-2002	2002-2005	2005-2009	2009-2014	2014-2017
[A] Δ *Employment-to-population* × *100*						
ICT Exposure	0.04	0.25^{*}	-0.50^{**}	0.03	-0.01	0.01
	(0.03)	(0.13)	(0.20)	(0.07)	(0.05)	(0.04)
SDB Exposure	-0.01	0.03	0.19	-0.10	-0.03	0.02
	(0.04)	(0.13)	(0.17)	(0.08)	(0.05)	(0.06)
R^2	0.61	0.71	0.72	0.81	0.90	0.81
Num. obs.	158	158	158	158	158	158
F statistic	12.99	20.03	21.55	34.17	72.85	35.05
[B] Δ *Average wage (in log)* × *100*						
ICT Exposure	-0.09	-0.41	0.76	0.15	-0.14	0.47^{***}
	(0.12)	(0.49)	(0.52)	(0.20)	(0.11)	(0.14)
SDB Exposure	0.12	0.05	-0.06	0.30	0.22^{*}	0.30^{*}
	(0.15)	(0.49)	(0.45)	(0.22)	(0.11)	(0.17)
R^2	0.63	0.59	0.78	0.72	0.90	0.59
Num. obs.	158	158	158	158	158	158
F statistic	13.92	12.03	30.05	20.70	72.81	12.08

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Clustered standard errors at NUTS1 between parentheses. This table summarizes the estimated coefficients for the IV regressions where the outcome variable is the annualized change in employment-to-population ratio (Panel A) and log-change in average wage (Panel B) over the digital technologies adoption life cycle and phases. The first column is the long-difference estimate for the entire period (1995–2017). The second and third columns correspond to the phases of the Web 1.0 cycle; the fourth and fifth columns correspond to the two phases of the Graphical User Interface and Cloud Computing cycle; and the last column corresponds to the first phase of the Big Data and AI cycle. Exposures to information and communication technology (ICT) and software and databases (SDB) are calculated using shift–share variables based on 1990 sectoral employment shares and then standardized. Panel A coefficients represent the percentage point change in the regional employment-to-population ratio for a one-standard-deviation increase in technology exposure during the cycle phase. Panel B coefficients indicate the corresponding percentage change in the regional average wage. Control variables include the log of the population in 1980, the change in robots, the change in the outcome variable in 1980–1994 to account for pre-trends, final demand, and trade exposure, respectively, over the cycle phase, and country fixed effects. Regressions are weighted by the population in 1990.

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

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

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

E Technological Cycles: Summarizing Major Developments

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

E.1 Web 1.0

Table E.1 outlines major technological developments during the Web 1.0 cycle (1990–2004). Advancements in mainframes and microcomputers began in the 1960s and 1970s. However, only with the reduction in price and size of microprocessors did personal computers become available for use in administrative tasks and smaller firms (Malerba et al. 1999, Freeman and Louçã 2001).[30] Concurrently, newer and more user-friendly operating systems like Windows 3.0 in 1990, Linux in 1991, and Windows 95 facilitated widespread adoption.

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

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

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

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

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

Notes: Own elaboration based on Lane (2019).

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

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

E.2 Graphical User Interface and Cloud Computing

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

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

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

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

E.3 Big Data and Artificial Intelligence

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

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

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

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

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

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

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

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

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

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

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