Pillars – Pathways to Inclusive Labour Markets

Report

The Adjustment of Labour Markets over Automation Cycles: An Analysis of European Regions

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The adjustment of labor markets over automation cycles: An analysis of European regions[*]

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Abstract

The paper examines the long-run *versus* short-run implications for labour markets of exposure to four automation technologies—robots, communication, information and software and databases. By applying a multiple break-point algorithm we identify investment cycles for each technology as affecting employment, wages, and wage shares for 163 NUTS-2 regions in 12 European countries over 1995-2017. In the long run, we find that robots have increased employment but reduced wages and the wage share in the region. ICT have had some positive impact on employment and wages, but mildly significant. Software and database have had a negative impact on employment, but no effect on wages. When we distinguish for shorter investment cycles, we find that the long run effect is concentrated in specific cycles, which often cancel out in the long run. For example, for robots the long-run positive effect on employment is driven by the investment during the downward cycle between 2006-2013.

Keywords: Automation, Investment cycles, Employment, Inequality.
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1 Introduction

Technological unemployment is an age-old concern in economics, which has recently re-surged in view of the latest waves of technological progress. Mechanical automation is now accompanied by several families of digital automation technologies, among which Robotization, Artificial Intelligence (AI), communication, information technologies and the increasing investments in software and data base that complement hardware digital infrastructures and feed AI (see Ciarli et al. 2021). Each of these technology families might have different effects on labour markets (Savona et al., 2022), including employment, wages and the wage share. The literature has not offered unanimous evidence, even when focusing on specific technologies such as robots and ICT.

For instance, while some of the studies on the regional of robots point at a positive effect on employment (Dauth et al. 2021, Bachmann et al. 2022), other studies find a negative effect (Acemoglu and Restrepo 2020,Chiacchio et al. 2018, Aghion et al. 2019) although limited in size (Benmelech and Zator 2022). In an attempt to understand these divergent results for European regions, Antón et al. 2022 argue that the negative implications on employment come from the period that goes from 1995-2005, while from 2005-2015 it turns positive.

Alongside the specific technical features, one of the reasons why the evidence on the impact of automation on labour markets is heterogeneous is because studies focus on different periods, characterised by different cycles of investments. For instance, seminal work on Information and Communication Technologies (ICTs) Freeman and Perez 1988) has shown that in Europe the largest growth rates in ICTs investments occurred at the beginning of the 1980s, and again at the end of the 1990s, before the dot.com bubble (Van Ark 2002).[1] In contrast, it is argued that investments in robots have been comparatively smaller that ICTs, and concentrated in fewer sectors and firms Benmelech and Zator 2022.[2] Beyond the size of investment, different investment cycles may also be characterised by different technology vintages, which are more or less likely to substitute/complement different working tasks. Technology also advance in waves with some periods characterised flurries of innovations, and others focused on adopting and adapting existing technologies (Silverberg and Verspagen 2003).

In addition, investments in technologies is lumpy (Doms and Dunne 1998, Cooper et al. 1999) and automation technologies are no exception (Domini et al., 2021; Bessen et al.,

[1] For detailed information on ICTs and software growth rates over 1980-2000, see Van Ark (2002).

[2] For what concerns wages, there are possibly more confounding factors, such as the role of institutional changes over time: it has been argued that de-unionization and in general the increase of large employers power has been the main determinant of wage suppression in the US since mid-1990s, when compared with investments in robotization (Mishel 2022; Dosi et al. 2021).

2022). Firms need time to adjust to the new technology in the production process and adapt skills through training or switching workers (Ciarli et al. 2021). The impact of investment on firm employment decisions takes time to materialize. Given the time requirement by firms to adapt and learn about new technology, productivity may immediately reduce to increase in a later stage (Gradzewicz 2021). As a result, the impact of current and past investments may differ. For example, over the long-run employment may benefit from an increase in productivity due to past automation cycles (Gregory et al. 2022), while workers may be replaced as firms adjust to the new technology.

This paper makes several contribution to the existing literature. First, we explain the "smoothed" long term effects of different automation technology on labor markets that we observe over the 20 years breaking down the shorter impacts over the varying investment cycles. Second, we distinguish between contemporaneous and lagged impacts, considering that firms and workers take time to adjust to new technologies, and that. Third, we distinguishing between different technologies—robots, IT, CT and software and database—which are complementary in terms of the investment behavior, but which are designed for different tasks. We thus analyze the impact of these four technologies on regional employment (employment-to-population ratio), wages and wage share, over the period 1995-2017, and for different technology investment cycles.

We conduct our analysis at the regional level including 163 NUTS-2 regions from 12 European countries over the period 1995 to 2017. The database merges several sources. Information on ICTs and software and databases comes from the EUKLEMS (Release 2021), while data on robots from the International Federation of Robotics (IFR). We estimate regional exposure to each technology by applying a shift-share design, in line with the literature on the topic (Acemoglu and Restrepo 2020, Dauth et al. 2021, Aghion et al. 2019, Chiacchio et al. 2018). To account for endogeneity issues, we instrument automation technologies in European regions with data on the US. We first analyze the long-run implications of these automation technologies on labor variables. Information on labor market outcomes —employment-to-population ratio, average wages, and wage share— is derived from the ARDECO database (Release 2021). Next, we identify investment cycles within the observed time period by applying a simultaneous estimation of multiple breakpoints following the methodology proposed by Bai and Perron (2003).[3] We then proceed to study the labor adjustments along these different periods, distinguishing between current and past investment effects.

[3] Given that investment is influenced by other confounding factors, we apply the algorithm over the times series cleaned from the effect of business cycles —proxied by real consumption— and from the long-run trend.

We offer a set of interesting findings, the most salient being:
First, long terms impacts (20+ years) of automation technologies on the labor market hides substantial impacts over shorter term investment cycles that cancel out in the long run.

Second, although short term investment cycles between robots, ICT and software and database are correlated, their impact on employment, wages and the age share varies substantially across technologies.

Third, we find a positive long-run effect of robots on employment-to-population ratio, which is driven by the contemporaneous short-run impact during the downward investment cycle between 2006-2013. Robots seem to be negatively associated with employment only in the plateau cycle between 2002-2006.

Fourth, the impact of robots investment on employment and wages is cyclical. A positive contemporaneous impact during a given investment cycle remains positive also during the following investment cycle, when the contemporaneous impact becomes negative.

Fifth, the long term positive employment outcomes related to communication technologies are driven by the downward investment cycle that follows the dot-com crisis (2001-2006).

Sixth, short term investment cycles in information technologies have a contemporaneous counter-cyclical impact on averages wages.

The negative long-run effect of software and databases on employment comes from the sharp recovery in investment that happened between 2003-2009, right after the dot-com crisis.

The remainder of the paper is organized as follows, in Section 2 we describe the data sources and the methodology to estimate technology exposure at the regional level. In Section 3 we first show the long-run implications of automation technologies, followed by the adjustment over investment cycles. Lastly, in Section 5 we conclude and indicate path for future work.

2 Data

2.1 Sample

We analyze the impact of technology penetration on labor market outcomes for 163 NUTS-2 regions from 12 European countries between 1995 and 2017.[4]

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

2.2 Variables

Labor market. We consider three labor market outcomes at the regional level: employment, measured as employment-to-population ratio, i.e. the total number of employed persons aged 15-64 over the total population; wages, measured as the average yearly wage per worker (in thousands €2015), calculated as the total compensation divided by the level of employment; and the functional distribution of income, measured as the labor share, i.e. the ratio between total labor compensation and gross value added (in millions €2015). The three variables are constructed using the ARDECO database at the NUTS-2 level.

Exposure to automation technologies. We consider four automation technologies, as in Petit et al. (2022):

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

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

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

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

We use the number of robots currently in use (i.e. robot stock) in each sector at the country level from the International Federation of Robotics (IFR); see Jurkat et al. (2022) for a comprehensive review. Robots are present in only three sectors out of six: Industry (B-E), Construction (F), and Non-Market Services (O-U). Given that about 30% of the robots are not allocated to a sector, we distribute them proportionally according to the average share in each sector of the total number of robots in the country. Moreover, given that for some countries robots are not available at the sectoral level for a number of years, we estimate them using the average share for years for which there is data availability.[5]

[5] We use the same procedure as in Petit et al. (2022): we distribute the robots not classified to a sector following Acemoglu and Restrepo 2020. Although some studies do not distribute the robots not allocated to a sector (see Graetz and Michaels 2018, Dauth et al. 2021), in our case is better to do so to guarantee a harmonized series of robots that can be comparable once we aggregate our measure of technology exposure across sectors.

The data on ICT and software and database come from the EU-KLEMS database (Release 2021). We exploit the fact that this source provides data on these technologies separately. Therefore, we use the stock of communication equipment (i.e. communication technology), computing equipment (i.e. information technology), and computer software and databases (i.e. software-database) at the country-industry level.[6] Our measures of these technology stocks are the net capital stock (at constant €2015 prices) which is derived from the national accounts.[7]

We define sectors according to the NACE Rev.2 classification. As there is a break in the classification from Rev. 1.1 to Rev. 2 in 2008, we aggregate sections accordingly to have consistent sectors; see section A.1 in the appendix for further details on the compatibilization of sectors.

Control variables. As there are other factors that can affect regional labor market outcomes, we introduce two control variables to isolate the role of investment in automation. We control for changes in final domestic demand which are driven by the business cycle using the real consumption index from the Inter-Country Input-Output database.[8] Second, we account for the potential impact of trade and international competition controlling for imports from China using the OECD Trade in Value Added database.[9] Increasing penetration of trade with emerging countries has detrimental consequences on employment in manufacturing (Autor et al. 2013, Autor et al. 2015). Both control variables are computed at the regional level.

Instrument. To address the endogeneity in the relation between decisions to invest in automation and labor, we instrument investment in European regions using data on investment in the same automation technology in the U.S., which is also retrieved from IFR (robots) and EU-KLEMS (ICT and software and database).[10] When computing our instrument (see more details in subsection 3.1.1), we use employment by sector in 1980 from the Labor Force Statistics from the OECD to normalize the technology stock.[11]

[6]See O'Mahony and Timmer (2009) for a comprehensive review.

[7]For Ireland, the technology stocks are available at the country level but not at the sectoral one. We thus recover them by allocating the technology stocks at the country level to the sectors within the country. To do so, we use the share of the sector in the country's gross fixed capital formation.

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

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

[10]Sectoral data on robots is only available as of 2004 for the U.S. We impute data backwards using the same methodology described for European countries.

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

3 Long Run Labor Market Impacts

3.1 Empirical Strategy

3.1.1 Technology exposure

We first measure the exposure of a European region r to technology K between t and $t+h$ as the difference in the share of capital over labor $\left(\frac{K_i^{EU}}{L_i^{EU}}\right)$ in sector i between t and $t+h$, weighted by the regional employment share in sector i in 1980 $\left(\frac{L_{ri}^{EU}}{L_r^{EU}}\right)$. Formally:

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

where L_{ri} is the level of employment in sector i in region r in 1980, L_r is the level of employment in the region in 1980, $K_{i,t}^{EU}/L_i^{EU}$ is the level of technology stock in year t per thousand worker in 1980 in sector i at the country level.

3.1.2 Identification

We estimate the relationship between labor market outcome variables and technology exposure over the 1995-2017 period using the following specification:

$$(y_r)_{1995}^{2017} = \alpha + \sum_K \beta^K (Exposure_r^K)_{1995}^{2017} + X'\gamma + u_r, \quad (2)$$

where $(y_r)_{1995}^{2017}$ is the labor market outcome variable at the regional level; $(Exposure_r^K)_{1995}^{2017}$ is the technology exposure in that same region, for each of the four K technologies; X are control variables (including final demand and trade exposure). Note that we always control for all four technologies, given that investment in robot is not independent from investment in ICT and software and database. And viceversa.

The relation between investment in automation technology, employment and wages is endogenous. Decision to invest in automation technologies are related to the cost and availability of labour (Bachmann et al., 2022), including through labor market institutions (Presidente, 2022). Some of the determinates of both automation and labour, such as labor institutions at industry-region level, are not observable. And the measurement of automation technologies has several issues. As noted, not all robot are allocated to sectors. And measurement and accounting for tangible and non tangible capital such as ICT and software varies across countries and over time. Estimates from equation 2 are therefore likely to be biased. The direction of the bias will depend on which source of endogeneity prevails.

Controlling for real consumption (as a proxy to account for demand shocks) and trade, only partially mitigate the problem.

Following the instrumental variable strategy used in Acemoglu and Restrepo (2020) and Antón et al. (2022) we use technological investment in a different country, which is also relentlessly automatising production of goods and services: the U.S.[12].

We first build the exposure of European regions by taking the change in automation technologies in the US (shift), while keeping the initial employment shares from the European regions (share). The instrument is defined as:

$$(Exposure_r^{K,US})_t^{t+h} = \sum_{i \in I} \frac{L_{ri}^{EU}}{L_r^{EU}} \left(\frac{K_{i,t+h}^{US}}{L_i^{US}} - \frac{K_{i,t}^{US}}{L_i^{US}} \right), \tag{3}$$

where $K_{i,t}^{US}/L_i^{US}$ is the level of technology stock in year t (per thousand worker in 1980) in sector i in the US. By taking the changes in the technology in the US we capture exogenous changes in the technology which induce diffusion in a country similar to Europe. And we allocate the investment proportionality to the exposure of each region in 1980, based on their sectoral specialisation.

For each automation technology, we then use the following first-stage specification:

$$(Exposure_r^{K,EU})_{1995}^{2017} = \alpha + \beta (Exposure_r^{K,US})_{1995}^{2017} + \eta_c + u_r, \tag{4}$$

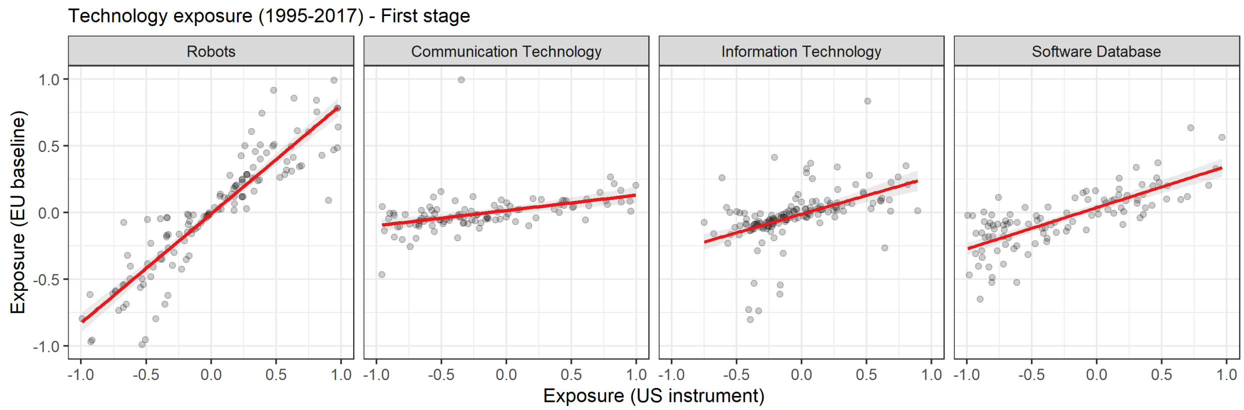
where $Exposure_r^{K,EU}$ is the baseline exposure to technology K in European region r between 1995 and 2017 as defined in Equation (1); $Exposure_r^{K,US}$ is the instrument as defined in Equation (3); and η_c is the country fixed effect. The country fixed effect accounts for between-country differences in technology stocks which are available for each industry at the national level. Figure 1 shows the relationship between the instrument and the instrumented variables (see Table B.1 in the appendix for first-stage regressions).

3.2 Results

Tables 1, 2, and 3 report results for the impact of each automation technology on, respectively, employment-to-population-ratio, average regional wage, and the wage ratio between 1995-2017, as estimated using equation 2 and instrumented using equation 3. We discuss each outcome in turn, for the four different automation technologies.

[12] An alternative approach used in the literature (Dauth et al., 2021; Aghion et al., 2019; Bachmann et al., 2022) is to employ other European countries. However, there are more common trends in employment between EU countries—especially through GVCs, and human capital flows— than between EU and the US. For instance, automation decisions in one country may alter labor supply in a neighbouring country

Figure 1: Technology exposure between 1995 and 2017 (First stage)



Notes: This figure presents the first-stage regressions for the technology exposure in European regions between 1995 and 2017 (y-axis) instrumented with the predicted exposure in the United States over the same period (x-axis). First-stage regressions are estimated separately for each automation technology with country-fixed effects. Both exposures are computed with a shift-share using the employment sectoral shares from European regions in 1980. For representation, both variables are plotted demeaned from country fixed-effects.

Table 1: Employment-to-population ratio and technology exposure (1995-2017)

	Dep. var.: % change in the emp-to-pop. ratio (1995-2017)			
	OLS - Baseline		2SLS - IV Second stage	
	(1)	(2)	(3)	(4)
1995-2017 ROB	1.32***	1.73***	1.30***	1.81***
	(0.35)	(0.37)	(0.35)	(0.37)
1995-2017 CT	0.12	0.34	0.77	1.78**
	(0.41)	(0.41)	(0.67)	(0.70)
1995-2017 IT	−0.31	−0.04	0.07	0.86*
	(0.33)	(0.34)	(0.46)	(0.50)
1995-2017 SDB	−0.07	−0.23	−0.38	−0.93***
	(0.20)	(0.20)	(0.32)	(0.34)
Final demand		Yes		Yes
Trade		Yes		Yes
R^2	0.12	0.18	0.13	0.21
Adj. R^2	0.10	0.14	0.11	0.18
Num. obs.	163	163	163	163

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio to robot, communication technology, information technology, and software database technology exposure. Technology exposure is constructed as a shift-share. Columns (1) and (2) refer to the baseline OLS estimate. Columns (3) and (4) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) and (4) include control variables which are changes in final domestic demand (measured with the real consumption index) and changes in trade exposure (measured with imports from China).

Employment-to-population ratio. Table 1 summarizes the impact of technology exposure on the employment-to-population ratio. Overall, robot penetration has a positive correlation with employment-to-population ratio which is consistent along both the OLS and the instrumented specifications. This result is different from what has been found in the US (Acemoglu and Restrepo, 2020), but consistent with some of the evidence emerging from European regions, such as Dauth et al. 2021 for Germany (driven by the increase in services), Antón et al. (2022) for several European countries up to 2015, and (Petit et al., 2022) for a larger number of countries. They are also in line with firm level evidence results from Finnald using an experimental design (Hirvonen et al., 2022) and firm level evidence explotiing investment spikes (Domini et al., 2021). Other studies finds more ambiguous results. Our estimates show that a 100% increase in the share of robots per worker has lead to a 2% increase in share of employees (over the working population).

Although ICT also show a positive impact, this is weakly significant and only in the IV specification when including all the controls. There is thus little evidence that ICT have had an impact on employment, when we also control for robots and software and databases.

Instead, the increased penetration of software and database seem to have led to replacing more jobs than it creates. This is also the technology that has grown most between 1995 and 2016, which is mainly used in services, were most of the workers are employed.

As we show in Petit et al. (2022), whereas an increased penetration of robots in industry is related to an increase in jobs in other sectors (see also Dauth et al. 2021), investment in database and software is not followed by employment creation in other service sectors.

Average wage and wage share Table 2 summarizes the relationship between technology exposure and average wage. 3 summarizes the relationship between technology exposure and the wage share. Despite the positive impact on employment, we observe a negative relationship between robot exposure and average wages, which also leads to a reduction in the wage share, i.e. a more unequal distribution between capital and wages.[13]

We find little evidence that over the more than 20 years period regions with higher investment in ICT and software and database have experienced a change in wages or the wage share. If at all, we observe a positive relation for ICT, but this is also too heterogenous across regions to be strongly significant. There is no long-run correlation between software and database and average wages, and this is observed in all models.

Summary on long run labor market impacts In sum, we observe very different effects on labor market outcomes between the different technologies. Despite robots being adopted mainly in industry, it is the only automation technology that has induced significant impacts

[13]This result is consistent with the finding on German local labor markets in Dauth et al. 2021, but not with the findings across countries in Graetz and Michaels (2018).

Table 2: Average wage and technology exposure (1995-2017)

	Dep. var.: % change in average wage (1995-2017)			
	OLS - Baseline		2SLS - IV Second stage	
	(1)	(2)	(3)	(4)
1995-2017 ROB	-1.44^{**}	-1.22^{**}	-1.75^{***}	-1.58^{***}
	(0.57)	(0.57)	(0.58)	(0.57)
1995-2017 CT	1.29^{*}	1.64^{***}	1.31	2.10^{*}
	(0.66)	(0.63)	(1.07)	(1.08)
1995-2017 IT	0.42	1.00^{*}	0.44	1.28^{*}
	(0.54)	(0.53)	(0.74)	(0.77)
1995-2017 SDB	−0.21	−0.34	−0.21	−0.55
	(0.32)	(0.31)	(0.51)	(0.53)
Final demand		Yes		Yes
Trade		Yes		Yes
R^2	0.20	0.32	0.21	0.33
Adj. R^2	0.18	0.29	0.19	0.31
Num. obs.	162	162	162	162

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the average wage to robot, communication technology, information technology, and software database technology exposure. Technology exposure is constructed as a shift-share. Columns (1) and (2) refer to the baseline OLS estimate. Columns (3) and (4) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) and (4) include control variables which are changes in final domestic demand (measured with the real consumption index) and changes in trade exposure (measured with imports from China).

on both employment (positive), wages (negative) ad the wage share (negative) across regions in Western Europe over the long run (1995-2017). As documented in Petit et al. (2022), these effects are a combination of what happens in the industry (mining, manufacturing and utilities), the sector that adopts most of the robots, and services, where employment also increases. New jobs are created in regions that increase most robots investment, but new jobs are paid relatively less (especially in industry (Petit et al., 2022)). This is consistent with the framework proposed by Sachs et al. (2015) where robot increase productivity, therefore demand and aggregate employment, but they also replace capital that is complementary to workers, and thus reduce wages.

Regions that invest more in intangible software and database, instead, replace more jobs than it creates in the industry in which the investment occurs or in other industries. But this has no significant effect on wages or the wage share. There is little evidence that ICT have a significant impact on in employment or wages, but it tends to be positive.

Although we capture only the more recent period in which most countries have experienced a reduction in the labor share (Karabarbounis and Neiman, 2013) and a decoupling

Table 3: Wage share and technology exposure (1995-2017)

	Dep. var.: pp. change in wage share (1995-2017)			
	OLS - Baseline		2SLS - IV Second stage	
	(1)	(2)	(3)	(4)
1995-2017 ROB	-0.91^{***}	-1.52^{***}	-1.00^{***}	-1.60^{***}
	(0.25)	(0.21)	(0.26)	(0.21)
1995-2017 CT	0.59^{**}	0.34	1.16^{**}	0.12
	(0.29)	(0.24)	(0.48)	(0.40)
1995-2017 IT	0.13	-0.13	0.47	-0.27
	(0.24)	(0.20)	(0.33)	(0.29)
1995-2017 SDB	-0.22	-0.01	-0.49^{**}	0.10
	(0.14)	(0.11)	(0.23)	(0.20)
Final demand		Yes		Yes
Trade		Yes		Yes
R^2	0.10	0.45	0.12	0.47
Adj. R^2	0.08	0.43	0.10	0.45
Num. obs.	162	162	162	162

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the wage share to robot, communication technology, information technology, and software database technology exposure. Technology exposure is constructed as a shift-share. Columns (1) and (2) refer to the baseline OLS estimate. Columns (3) and (4) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) and (4) include control variables which are changes in final domestic demand (measured with the real consumption index) and changes in trade exposure (measured with imports from China).

between median wages and labour productivity (Stansbury and Summers, 2017), our analysis point to only one automation technology that may be partly driving the fall in the wage share: robots. As robots are adopted mainly by the largest (Acemoglu et al., 2022) and most productive firms (Stiebale et al., 2020), it is also possible that robot adoption is followed by further market concentration in superstar firms that increase employment, but less than productivity, and are also the main driver of the reduction in the labour share (Autor et al., 2020).

While it is very important to measure the implications of automation technologies over the long-run, we also know that in the long run there are many compensation forces that cancel out impact on employment (Calvino and Virgillito, 2018), and occupation levels remain relatively stable (Autor, 2015). We though know very little about what happens in the short run, when investment in new technologies accelerate or slow down. The adoption of automation technologies changes over time, in relation to changes in the technology themselves, and their relative cost. For example, we know from the literature that ICT and software and databases have grown faster in the second half of the 1990s, and that this contributed to an increase in productivity until 2004 (Van Ark 2016). In Europe, for instance, results on the impact of robots on employment across regions depend on the period considered, as shown in (Antón et al., 2022). In the next section we identify investment cycles and identify how whether the long term small adjustments hide larger short term labor market adjustments.

4 Labor Market Impacts Over Investment Cycles

4.1 Empirical Strategy

4.1.1 Investment Cycles in Europe

To study the impact on labour markets of short run changes in automation technologies, we first identify investment cycles from the data, instead of using arbitrary break points. We estimate automation technologies cycles at the European level between 1995 and 2017. We start with the technology stock (per thousand workers in 1980) aggregated at the European level (see Figure A.1 in the appendix). The four automation technologies experience a linear and increasing trend in Europe over the period.

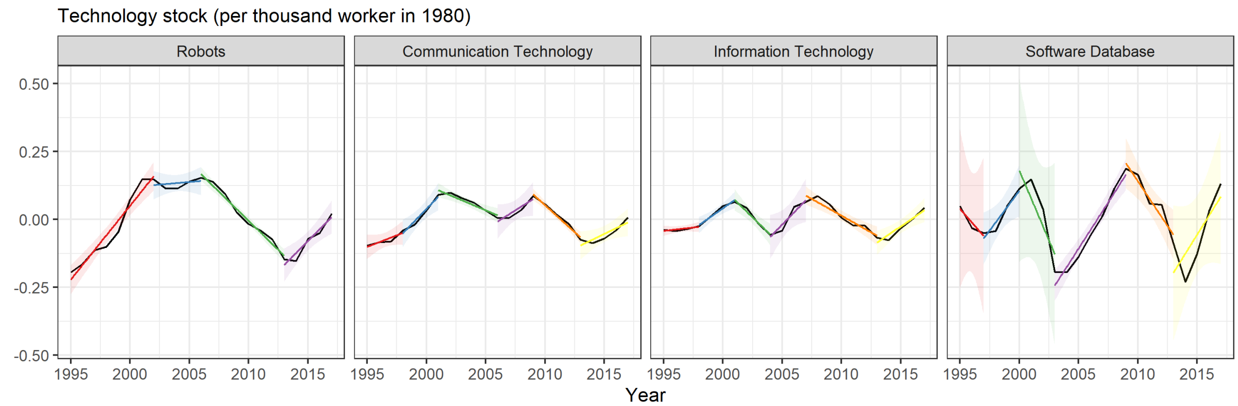
These investment patterns are the result of two confounding factors. First, the observed trajectories in technology penetration are affected by business cycles since investments are pro-cyclical. Second, the observed trajectories are also subject to long-run structural changes.

We neutralize both latter effects to observe the real investment cycles in automation technologies. To do so, we regress the technology stock (per thousand workers in 1980) on the real consumption expenditure—which accounts for business cycles—and on a linear trend—which accounts for the long-run trend. Both the technology stock and real consumption expenditure are aggregated at the European level. By taking the residuals, we obtain the real investment cycles in robots, communication technology, information technology, and software and database.

To determine the aggregate cycles, we look for structural breaks in time series. We perform a simultaneous estimation of multiple breakpoints (see Bai and Perron (2003)). For each technology K, we split the time series into m cycles (i.e. segments).

Figure 2 shows the investment cycles for the four automation technologies. Despite robots showing fewer cycles than ICT and databases, they tend to be quite similar, showing some complementarity between them. ICT and software and database follow a very similar pattern. An increased investment at the beginning of the period driven mainly by falling prices (Doms, 2004), reaching a peak right after the dot-com crisis in 2000, a crisis driven by

Figure 2: Investment cycles between 1995 and 2017



Notes: This figure shows the investment cycles in robots, communication technology, information technology and software and databases. We take the residuals after regressing each technology stock by real consumption index and a time trend. We next apply to each technology a simultaneous estimation of multiple breakpoints following Bai and Perron (2003) to split the series into m cycles (i.e. segments). As a result, robots have four cycles, while ICT and software and databases have six.

over-investment in ICT, especially in communication and internet.[14] The consequences of the crises are felt in the following downward trend that goes until 2003-2006 depending on the technology. This slow down is followed by renewed advances in ICT, which spur a recover in investment which last until the 2007 crisis, which in this case is financial. The effect o th financial crisis last a little bit longer, with European investment in ICT accelerating again since 2013.

In spite of the similarity in the direction of the cycles, there is a remarkable difference in the size of software and database cycles with respect to ICT. Cycles are more pronounced for software and database than for ICT and viceversa.[15] What is also interesting is that the trends observed in Figure 2 do not follow the path of the average price in hardware and communication technology that have sharply decreased in many advanced economies, so investment cycles do seem to be driven by their cost reduction.[16]

The cycles for robots are related to what happens in ICT (showing the complementarities), but lagged by a few periods. Investments in robots respond less to the dot-com bubble: as ICT fall, investment in robots also grows more slowly, and settles on a plateau. The slowdown comes only later (2006), with a five years lag with respect to ICT. But, unlike for ICT

[14]This is consistent with Van Ark (2016), who find that the share of ICT investment as a percentage of the GDP peaks around the 2000s for Germany, United Kingdom and the U.S. It is also consistent with the cycles documented by the OECD: https://www.oecd-ilibrary.org/docserver/sti$_s coreboard - 2009 - 17 - en.pdf?expires = 1672081818id = idaccname = guestchecksum = 9BEF5F5F6AC25F93931AC6D7FD8CD8C3$

[15]This can be related to the fact that there has been a greater increase in volume in software and databases in comparison to communication and hardware technologies over the period 1995-2015 (OECD 2019), but also to the flexibility of investing in intanigle assets, rather than physical capital.

[16]Refer to OECD (2019) for the trends in several OECD countries.

there is no sign of recovery until 2013: the slowdown in robots investment starts well before the financial crisis, and lasts throughout it.

4.1.2 Shift-share decomposition

We estimate the exposure between 1995 and 2017 using a shift share design—as described in Equation (1). Let the year $t+h'$ be the breakpoint—i.e. any intermediate year between 1995 and 2017—which splits the whole period into two cycles (i.e. sub-periods). We can split the exposure between: the cycle *before* the breakpoint and the cycle *after* the breakpoint such that

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

Regrouping terms and using the exposure definition from Equation (1), we can rewrite the total exposure as the sum of both cycle exposures:

$$(Exposure_r^K)_{1995}^{2017} = \underbrace{\sum_{i \in I} \frac{L_{ri}}{L_r} \left(\frac{K_{i,2017}}{L_i} - \frac{K_{i,t+h'}}{L_i} \right)}_{\equiv (Exposure_r^K)_{w_2}} + \underbrace{\sum_{i \in I} \frac{L_{ri}}{L_r} \left(\frac{K_{i,t+h'}}{L_i} - \frac{K_{i,1995}}{L_i} \right)}_{\equiv (Exposure_r^K)_{w_1}},$$

where w_1 refers to the technology cycle between 1995 and $t+h'$ and w_2 to the one between $t+h'$ and 2017. The split of exposure can be generalized to any number of cycles such that

$$(Exposure_r^K)_{1995}^{2017} = \sum_{w \in W} (Exposure_r^K)_w. \tag{5}$$

4.1.3 Identification

We estimate the labor market adjustments to the exposure to an automation technology K during the different investment cycles of that technology. To do so, we consider the following specification:

$$(y_r)_w = \alpha_w + \beta_w^K \times (Exposure_r^K)_w + X'\gamma + u_r, \tag{6}$$

where $(y_r)_w$ is the outcome variable in the region r over the cycle w, $(Exposure_r^K)_w$ is the exposure to technology K in that same region over the same cycle, and X are control variables (such as final demand, trade exposure, and exposure to other technologies) including cycle fixed effects. We instrument the technology exposure with our IV shift-share as in Equation (4) for each technology investment cycle separately. In an extended specification, we also control for the lagged adjustments of labour market by including a lagged term of the exposure $((Exposure_r^K)_{w-1})$

Table 4: Adjustments to robot exposure during robot investment cycles

	Investment cycles (w)			
	1995-2002	2002-2006	2006-2013	2013-2017
Emp-to-pop. ratio				
Exposure$_w$	3.54^{***}	-1.01	10.01^{***}	-1.76^{**}
	(0.63)	(1.07)	(0.78)	(0.83)
Average wage				
Exposure$_w$	-5.92^{***}	-6.58^{***}	2.16^{**}	1.20
	(0.88)	(1.49)	(1.09)	(1.16)
Wage share				
Exposure$_w$	-0.45	-2.83^{***}	1.15^{**}	-0.40
	(0.39)	(0.67)	(0.49)	(0.52)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to robots during investment cycles in this technology. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.2 to B.4 in the appendix show the detailed specifications.

4.2 Results

We present the results by automation technologies. We only report the coefficients from the second-stage regressions from the IV shift-share with the full set of controls. First stage and baseline regressions are available in the appendix.

Robot. We start with the four robot cycles. As depicted in Figure 2, robot investment increases over the period 1995–2002, then it flattens until 2006 before declining between 2006 and 2013, and finally, it increases until the end of the sample period.

Table 4 summarizes the labor market adjustments to robot exposure during the four robot investment cycles. We report the coefficients from the second-stage regression of the IV shift-share with the full set of controls.[17]

The impact of robot exposure on employment (positive) and wages (negative) is significant in the first cycle during which there is a sharp increase in robots investment (1995-2002), but there is no impact on the wage share. The wage share is negatively impacted mainly during the plateau, when there is no increase in employment and only a negative impact on wages (2002-2006). During the period of slow increase in robots investment (2006-2013), possibly driven mainly by replacement of existing capital with new vintages, regions that

[17]Predicted technology exposures are obtained from the first-stage regression, see Figure C.1 in the appendix. Tables B.2, B.3 and B.4 in the appendix present the baseline and second-stage regressions for, respectively, the employment-to-population ratio, average wage and wage share.

Table 5: Adjustments to communication technology exposure during CT investment cycles

	Investment cycles (w)					
	1995-1998	1998-2001	2001-2006	2006-2009	2009-2013	2013-2017
Emp-to-pop. ratio						
Exposure$_w$	-0.78	-0.52	3.67^{***}	-0.39	-5.48^{***}	0.08
	(0.85)	(0.79)	(1.40)	(1.32)	(1.50)	(0.77)
Average wage						
Exposure$_w$	3.30^{***}	5.73^{***}	18.65^{***}	-5.83^{***}	7.71^{***}	-0.79
	(1.24)	(1.16)	(2.04)	(1.93)	(2.19)	(1.12)
Wage share						
Exposure$_w$	-1.15^{**}	2.40^{***}	5.88^{***}	-0.55	-0.07	-0.18
	(0.57)	(0.53)	(0.93)	(0.89)	(1.00)	(0.52)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to communication technology during investment cycles in this technology. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.8 to B.10 in the appendix show the detailed specifications.

invest most in robots experience an increase in both employment and wages (and a small increase in the wage share)[18]. During the most recent increase in robots investment, we observe an overall negative impact on employment. In sum, the long term positive impact on employment (Section 3) is driven mainly by the slowest investment cycle between 2006-2013, whereas the negative impact on wages is due to the higher investment cycle in the 90s and the flatter cycle over the turn of the century.

Communication technology. There are five communication technology investment cycles. As depicted in Figure 2, CT investment increases from 1995 to 2001—with a steeper slope from 1998—before declining until 2006 where it reaches a trough. After 2006, investment increases until 2009 before declining again to reach a second trough in 2013. Lastly, investment increases until the end of the period.

Table 5 summarizes the labor market adjustments to communication technology exposure during the six CT investment cycles. We report the coefficients from the second-stage regression of the IV shift-share with the full set of controls.[19]

As noted in Section 3, communication technology does not have a highly significant impact on employment nor wages in the long run. Table 5 confirms that investment in com-

[18]These results are in line with Antón et al. (2022) who find a negative effect for 1995–2005—in our case this is reflected in the 2002–2006 cycle—and a positive effect for the period 2005-2015—which in our case is reflected in the 2006-2013 cycle.

[19]Predicted technology exposures are obtained from the first-stage regression, see Figure C.2 in the appendix. Tables B.8, B.9 and B.10 in the appendix present the baseline and second-stage regressions for, respectively, the employment-to-population ratio, average wage and wage share.

Table 6: Adjustments to information technology exposure during IT investment cycles

	Investment cycles (w)					
	1995-1998	1998-2001	2001-2004	2004-2007	2007-2013	2013-2017
Emp-to-pop. ratio						
Exposure$_w$	4.91***	-3.13^{*}	-0.90	0.69	-6.27^{***}	-0.27
	(1.80)	(1.89)	(1.40)	(0.48)	(0.98)	(0.57)
Average wage						
Exposure$_w$	12.12***	13.62***	7.12***	1.43**	2.70**	-0.88
	(2.46)	(2.58)	(1.92)	(0.66)	(1.34)	(0.78)
Wage share						
Exposure$_w$	1.13	4.47***	2.50***	1.54***	-1.72^{***}	-0.45
	(1.11)	(1.16)	(0.86)	(0.30)	(0.60)	(0.35)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to information technology during investment cycles in this technology. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.14 to B.16 in the appendix show the detailed specifications.

munication technology does not have much effect on employment as it is only significant in the downward phases of 2001-2006 and 2009-2013 with positive and negative signs respectively, which cancel out in the long run. The results on wages and the wage share are quite stable along the different phases. Although the positive effect on average wages in Table 2 is weakly significant, we observed a positive impact in most of the investment cycles.

Information technology. There are six information technology investment cycles. As depicted in Figure 2, IT exhibits the same investment cycles as CT although more volatile. Investment increases between 1995 and 2001—intensifying after 1998—, then declines until 2004 and reaches a peak in 2007 before declining again to reach a trough in 2013. Lastly, investment is still growing at the end of the sample in 2017.

Table 6 summarizes the labor market adjustments to information technology exposure during the six IT investment cycles.[20] As for CT, the weakly significant positive effect on employment in the long-run displayed in Table 1 is due to a positive impact of the first high growth cycle (1995-1998) and a negative impact during the most recent downturn (2007-13). The results on average wages and labor share do not seem to depend on the phase of the cycle. In the first four periods, the effect of IT investment on average wage is positive and significant—with coefficients reducing size along time—and it is also positively correlated with labor share. The downturn of 2007-2013 is associated with a positive implication on

[20]Predicted technology exposures are obtained from the first-stage regression, Figure Table C.3 in the appendix. Tables B.14, B.15 and B.16 in the appendix present the baseline and second-stage regressions for, respectively, the employment-to-population ratio, average wage and wage share.

Table 7: Adjustments to software database exposure during software database investment cycles

	Investment cycles (w)					
	1995-1997	1997-2000	2000-2003	2003-2009	2009-2013	2013-2017
Emp-to-pop. ratio						
Exposure$_w$	0.44	0.16	3.09***	-0.78^{***}	0.13	0.29
	(1.29)	(0.52)	(1.10)	(0.23)	(0.38)	(0.59)
Average wage						
Exposure$_w$	-6.54^{***}	-3.03^{***}	-8.97^{***}	0.42	-1.03^{*}	0.89
	(1.95)	(0.78)	(1.66)	(0.34)	(0.57)	(0.89)
Wage share						
Exposure$_w$	1.27	-0.82^{**}	-2.05^{***}	-0.73^{***}	0.29	0.21
	(0.91)	(0.36)	(0.78)	(0.16)	(0.27)	(0.41)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to software and databases during investment cycles in this technology. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.20 to B.22 in the appendix show the detailed specifications.

average wages and a reduction of the wage share —probably explained by an increase in productivity. As for CT, the positive impacts that we observe in the shorter period fail to show up in the longer run. This is probably due to the fact that we observe such positive impacts both during upward and downward cycles.

Software database. There are six software database investment cycles as depicted in Figure 2. SDB investment cycles display the same patterns as ICT, although less volatile. It starts by declining until 1997 before reaching a first peak in 2000. The next trough occurs in 2003 before reaching a second peak in 2009. Lastly, SDB investment declines until 2013 before increasing again until the end of the sample period.

Table 7 summarizes the labor market adjustments to software database technology exposure during the six software-database investment cycles.[21] The phases in which there is a deceleration of investment in software and databases are associated with positive implications for employment, but this is only significant after the dot-com bubble. Interestingly, the recovery that follows has negative implications on the employment ratio. Unlike what we observe for ICT, the first three periods and the cycle related to the crisis are associated with negative coefficients for average wages. In the case of this technology, the dot-com crisis is related to both negative implications on average wages and labor share. Overall, we do not observe in the short run cycles the negative impact on employment that we find for the long

[21]Predicted technology exposures are obtained from the first-stage regression, see Table C.4 in the appendix. Tables B.20, B.21 and B.22 in the appendix present the baseline and second-stage regressions for, respectively, the employment-to-population ratio, average wage and wage share.

run changes in investment. The long run impacts also hide the short run negative impacts on wages during first three cycles before and after the dot-com bubble burst.

4.3 Delayed adjustments

Firms require time to integrate new technologies in the production process, which may have implications for workers in the following years. Labor market adjustments to automation technologies are not necessarily contemporaneous to the investment and may appear only several years thereafter. For instance, Van Ark (2016) highlights the fact that the dramatic increase in ICT and software investment in the early 1990s was not initially translated into productivity gains until the second half of the decade. Using the investment cycles in the automation technologies observed in Figure 2, we account for the lag effects in labor market adjustments to automation by considering the impact of technology exposure in the previous automation cycle on labor outcomes in the current cycle. We estimate the following specification:

$$(y_r)_w = \alpha + \beta_w^K \times (Exposure_r^K)_w + \delta_w^K \times (Exposure_r^K)_{w-1} + X'\gamma + u_r, \tag{7}$$

where $(y_r)_w$ is the outcome variable in the region r over the cycle w, $(Exposure_r^K)_w$ is the exposure to technology K in that same region over the same cycle, $(Exposure_r^K)_{w-1}$ over the previous cycle, and X are control variables (such as final demand, trade exposure, contemporaneous and delayed exposure to other technologies) including cycle fixed effects. We instrument the technology exposure with our IV shift-share as in Equation (4) for each technology investment separately.

Robot. Table 8 shows the effects on labor outcomes controlling for the previous investment cycles. Results change substantially in relation to Table 4 when we did not control for the effect of past cycles. During the plateau of 2002-2006, we observe two opposite effects on employment-to-population ratio. While there is a negative and significant effect of the current cycle, this is partially counterbalanced by a positive effect coming from the lagged upward cycle (although the specification was different, the impact on the 1995-2002 cycle is positive in Table 4). There is a non-significant effect on wages for both current and previous investment cycles. The wage share shows a similar dynamic to employment.

The decrease cycle of 2006-2013 is associated with a positive employment effect that is partially compensated by the past cycle effect that continues to be negative. This employment creation is also positively correlated with an increase in average wages. The recovery of robot investment adverted for the period that goes from 2013 to 2017 is associated with

Table 8: Contemporaneous and delayed adjustments to robot exposure during robot investment cycles

	Investment cycles (w)		
	2002-2006	2006-2013	2013-2017
Emp-to-pop. ratio			
Exposure$_w$	-25.67^{***}	11.18^{***}	6.30^{*}
	(6.63)	(0.88)	(3.80)
Exposure$_{w-1}$	14.13^{***}	-7.97^{***}	-6.93^{*}
	(3.47)	(1.03)	(3.61)
Average wage			
Exposure$_w$	-2.76	3.29^{***}	-12.81^{***}
	(8.04)	(1.07)	(4.60)
Exposure$_{w-1}$	-1.02	2.96^{**}	14.71^{***}
	(4.21)	(1.24)	(4.38)
Wage share			
Exposure$_w$	-23.48^{***}	0.48	-7.59^{***}
	(4.02)	(0.54)	(2.30)
Exposure$_{w-1}$	11.62^{***}	-1.55^{**}	7.93^{***}
	(2.11)	(0.62)	(2.19)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to robots during investment cycles in this technology including current w and past cycle effects $w-1$. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.5 to B.7 in the appendix show the detailed specifications.

a decrease in employment-to-population ratio, mainly explained by the past cycle which has a negative but weak effect. Although results for average wage and labor share are not significant, when including lagged effects Table 8 shows that the current and past cycle effects go in the opposite direction as employment. In these cases, the adjustment is driven by the previous cycle.

In sum, the impact of a robot cycle has an impact on employment that last also in the following cycle with the same sign, but coefficients tend to be smaller and the effect of the current investment prevails. The overall effect during a cycle is thus driven by the current impact, while still absorbing adjustments from the earlier investment cycle.

Table 9: Contemporaneous and delayed adjustments to communication technology exposure during CT investment cycles

	Investment cycles (w)				
	1998-2001	2001-2006	2006-2009	2009-2013	2013-2017
Emp-to-pop. ratio					
Exposure$_w$	5.71*	-1.39	-19.03^{***}	-14.96^{***}	-0.18
	(3.38)	(1.86)	(3.57)	(1.75)	(1.32)
Exposure$_{w-1}$	-3.22	2.96	20.98***	0.45	-2.58
	(3.12)	(3.21)	(2.77)	(1.94)	(1.93)
Average wage					
Exposure$_w$	-10.49^{**}	16.51***	23.73***	11.51***	4.02**
	(4.90)	(2.70)	(5.18)	(2.54)	(1.91)
Exposure$_{w-1}$	9.20**	3.13	-28.54^{***}	-17.93^{***}	-13.00^{***}
	(4.52)	(4.65)	(4.01)	(2.81)	(2.80)
Wage share					
Exposure$_w$	4.64**	2.60**	8.44***	-1.93^{*}	1.51*
	(2.24)	(1.23)	(2.37)	(1.16)	(0.87)
Exposure$_{w-1}$	-3.28	6.91***	-4.73^{***}	-4.18^{***}	-5.68^{***}
	(2.06)	(2.12)	(1.83)	(1.28)	(1.28)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to communication technology during investment cycles in this technology including current w and past cycle effects $w - 1$. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.11 to B.13 in the appendix show the detailed specifications.

Communication technology. Table 9 shows the effects on labor outcomes controlling for the previous investment cycles for this technology. The results of employment-to-population ratio are heterogeneous. We observe a negative implication on employment during the downward trend of 2009-2013 that is mainly driven by the current cycle effect.

Investment in communication technologies has significant correlations with average wages, but this pattern is not associated with the direction of the cycle. In the last three cycles, there is a positive association between the present cycle and CT investment and the opposite holds for the lagged effects.

Something similar happens when looking at the consequences on wage share, where there is no clear pattern with the communication cycle. By contrast, we observe that for the first cycle the contemporaneous effect is positive and it tends to prevail, while for the last two the lagged effect is the predominant one.

Table 10: Contemporaneous and delayed adjustments to information technology exposure during IT investment cycles

	Investment cycles (w)				
	1998-2001	2001-2004	2004-2007	2007-2013	2013-2017
Emp-to-pop. ratio					
Exposure$_w$	11.18	6.82	7.60***	−10.19***	3.16***
	(8.27)	(5.51)	(2.28)	(1.27)	(1.00)
Exposure$_{w-1}$	−3.80	−1.73	8.35**	4.49***	−12.16***
	(6.48)	(3.05)	(3.63)	(0.77)	(2.28)
Average wage					
Exposure$_w$	−35.94***	13.12*	−0.24	3.41**	−2.98**
	(11.11)	(7.40)	(3.06)	(1.71)	(1.34)
Exposure$_{w-1}$	30.57***	−1.59	−7.09	−8.34***	0.15
	(8.71)	(4.10)	(4.88)	(1.04)	(3.06)
Wage share					
Exposure$_w$	3.05	4.35	−0.33	−1.73**	−2.34***
	(5.67)	(3.77)	(1.56)	(0.87)	(0.68)
Exposure$_{w-1}$	−0.36	−2.17	1.33	−0.31	−6.43***
	(4.44)	(2.09)	(2.49)	(0.53)	(1.56)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to information technology during investment cycles in this technology including current w and past cycle effects $w-1$. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.17 to B.19 in the appendix show the detailed specifications.

Information technology. The weak negative effect observed for IT during the upward cycle of 1998-2001 disappears when controlling for past cycles. Actually, IT starts evidencing some significant implications on employment as of 2004. From this point, we observe that when IT investment increases (2004-2007 and 2013-2017), there is a positive contemporaneous effect on employment-to-population. However, in both cases, the overall effect is dominated by past cycles, which are positive and negative respectively. By contrast, during the decreasing cycle between 2007-2013, a negative relationship is observed between IT penetration and employment, mainly driven by the current cycle. Although Table 6 reflects a positive effect on averages wages, Table 10 unpacks a countercyclical relationship between average wages and current IT investments. When IT investment is expanding, there is a decrease in wages and the other way around. Moreover, in most of the cycles the contemporaneous effect dominates When controlling for the previous cycles the effect of IT investments are, in general, not significant.

Table 11: Contemporaneous and delayed adjustments to software database exposure in software database investment cycles

	Investment cycles (w)				
	1997-2000	2000-2003	2003-2009	2009-2013	2013-2017
Emp-to-pop. ratio					
Exposure$_w$	-3.65^{**}	3.57^{*}	-1.16^{**}	-1.52	-1.89
	(1.77)	(2.08)	(0.53)	(0.98)	(1.37)
Exposure$_{w-1}$	3.82	-1.43	-9.34^{***}	0.31	2.52^{**}
	(4.15)	(1.72)	(1.35)	(0.52)	(1.13)
Average wage					
Exposure$_w$	9.90^{***}	-11.11^{***}	1.27	-0.20	2.48
	(2.67)	(3.14)	(0.80)	(1.48)	(2.07)
Exposure$_{w-1}$	-27.76^{***}	0.01	-0.79	3.29^{***}	-1.37
	(6.28)	(2.60)	(2.04)	(0.79)	(1.72)
Wage share					
Exposure$_w$	2.57^{**}	-2.55^{*}	-0.94^{**}	-0.39	3.21^{***}
	(1.29)	(1.51)	(0.39)	(0.71)	(1.00)
Exposure$_{w-1}$	-7.04^{**}	-0.21	1.55	1.16^{***}	-2.55^{***}
	(3.03)	(1.25)	(0.98)	(0.38)	(0.83)

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the employment-to-population ratio, average wages and wage share to software and databases during investment cycles in this technology including current w and past cycle effects $w-1$. Technology exposure is constructed as a shift-share. The coefficients refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Employment-to-population ratio and average wages are in log change and the rest are the change between the beginning and end of each cycle. Tables B.23 to B.25 in the appendix show the detailed specifications.

Software database. Software and databases are not strongly associated with changes in employment-to-population ratio. Nevertheless, during the downward trend right after the dot-com crisis, it is positively associated with employment and mainly explained by the effect of the current cycle. In the afterward recovery (2003-2009), the relation turns negative at the time that is driven the past cycle effect. The negative impact on employment observed in the long-run (1995-2017) seems to be driven by the upward cycles of 1997-2000 and 2003-2009. Initially, in Table 7 we observe a negative effect of software and database on wages in the first three cycles. As we control for the lags of previous cycles, Table 11 depicts an interesting story. On the one hand, when investment in SDB increases, there is a positive correlation with current cycles, although it is only significant before the dot-com (1997-2000) and compensated by a negative effect from the previous cycle. Conversely, during the downward phases the current cycle is negatively associated with average wages, but only significant during the dot-com bubble. Moreover, we also observe that the sign of the current cycle remains the same when including it as a lag in the following one (i.e. the positive effect of 1997-2000 remains positive when it is included as a lag in the 2000-2003 cycle). Concerning the implications of software and databases investments in labor share, we observe a procyclical movement for the current cycles, which sometimes is counterbalanced by the lagged effect.

5 Conclusion

The aim of this paper has been to explore the labour markets effects of automation technologies that are heterogeneous in their levels of maturity and penetration in regions and sectors and in their intensity of hardware and software: robots, information technology, communication technology and software and databases. We consider their different investment cycles, as we are interested in whether the features above are reflected in pro or countercyclical effects on labour markets. We breakdown the long-run (1995-2017) adjustments into sub-periods which are defined by different investment cycles in each of the technologies.

In order to identify investment cycles that are solely attributable to the emergence and penetration of each specific technology, we remove the effect of business cycles and time trends from the time series and we apply a Bai and Perron (2003) algorithm to find simultaneous breakpoints. We also look at the current and lagged effects of investment cycles to account for possible tails not otherwise detectable. We analyze the implications of investment cycles in the considered automation technologies on three labor market outcomes: employment-to-population ratio, average wages and labor share for 163 NUTS-2 regions in 12 European countries.

We observe that there are complementarities among the four technologies, as investment cycles are fairly similar. In particular, we observe an upward trend up to the beginning of the 2000s (with the exception of software and databases which slightly decrease first). Also, following the financial crisis, investments in all technologies start to recover from 2012 or 2013 onward.[22]

Our methodological approach allows us to identify the specific investment cycles that lead to the long-run pattern. In the case of *robots*, we find that the long-run positive effects on both employment to population ratio and wages are mainly driven by the downward investment cycle of 2006-2013; while a negative effect is observed in the stagnation of 2002-2006. In both cases, the results are driven by the current rather than the lagged effect. These results are in line with Antón et al. (2022), who find a negative effect for 1995-2005

[22] Our last wave is up to 2017 due to data availability, so it is worth mentioning that the actual wave may have been longer.

and a positive one for 2005-2015. Moreover, we also observe that the sign of the coefficient of the lagged effect is the same as the current effect of the previous cycle. In other words, the effect of cycles is transferred into the next period —with the exception of the last wave—. In the case of *communication technologies*, the downward trend of 2001-2006 that follows the dot.com bubble burst explains the positive labor outcomes, especially for average wages and wage share, whereas the downward trend that has followed the financial crisis (2009-2013) has negatively affected employment. This suggests that investment cycles of very different nature (dot.com bubble and the financial crash) have had respectively counter-cyclical and a pro-cyclical effects over wages and employment. Overall, the positive effect on employment observed in the long-run is mainly driven by the upward trend in 1998-2001. For what concerns *information technologies*, in the last three cycles — 2004-2007, 2007-2013 and 2013-2017— we detect a pro-cyclical behavior with respect to the current cycle effect on employment. Additionally, we observe that the effects continues in the following cycle. By contrast, we notice a counter-cyclical trend with respect to average wages and contemporaneous investment cycle.

Both Communication and Information technologies seem to behave similarly with respect to both the cycles (upward trends during the dot.com bubble and downward trend when this burst and the post financial crash downward trend) and with respect to the main labour market outcomes: pro-cyclical with respect to employment and counter-cyclical with respect to wages. The technological and financial natures of the cycles tend to have opposite effects on real (labour) and monetary (wages) labour market outcomes. Investment cycles in *Software and databases* seem to behave differently from the previous technologies: the overall negative effect on employment-to-population ratio is explained by the recovery post dot-com (2003-2009) (counter-cyclical effect). Unlike information and communication technology, a pro-cyclical relation between average wages and current cycle is observed —albeit not always significant. This seem to suggest that investments in software and database have responded differently or at least lagged, to the technological and financial bubbles, and have had opposite effects on labour market outcomes when it comes to their pro-cyclical and counter-cyclical effects.

Investments cycles responding to shocks of different nature (dot.com bubble and the financial crisis) characterise slightly differently robots, ICTs and software and database. In addition, employment and wage effects seem to be respectively pro- and counter-cyclical in general, though robots and the other three technologies seem to behave differently. Hence, It is not immediate to derive policy implications from our results. In the case of robots, for instance, policies should aim at mitigating the short-run negative implication on employment, but greater attention should be paid to the long-run negative effects on average wages and inequality. It is likely that a substantial attention should be paid to the structural role of labour market institutions, which are ultimately responsible for reducing the wage inequality effects, in line with

The present work has a number of limitations that could be addressed in future research. First, given the speed at which technologies have been changing over the past few decades, it could be argued that a positive (negative) investment cycle at the beginning of the time span —i.e. mid 1990s— may not have the same effect as a positive (negative) at the end of the period. Unfortunately, due to data constraints, we cannot account for changes in the quality of the technologies, which can also have an effect on labor adjustments. Second, there is some evidence suggesting that due to a greater fall in prices of ICT-related services, there has been a hollowing out of investment in these services (Van Ark 2016). This can also be impacting labor outcomes, that, again due to the lack of data on this we cannot verify.

Finally, there is certainly scope for future work, particularly on the qualitative investigation of the regional specificity of these trends. Considering that the pace of technology adoption is highly heterogeneous across European regions —as some regions adopted automation technologies at a later stage—, there is room to decompose the aggregate European cycles to identify potential different trends in investment that may lead to diverse labor outcomes. We intend to explore this in future work.

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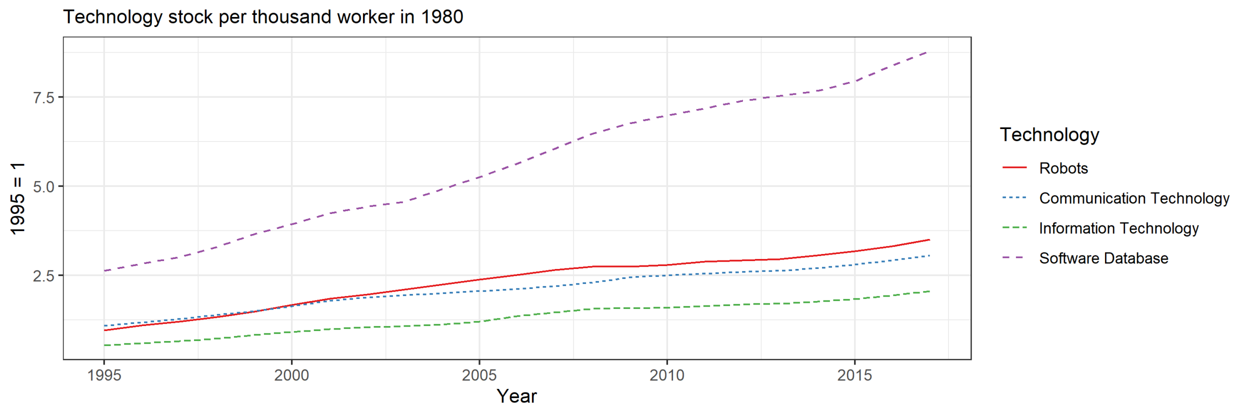
Appendices

A Appendix A

Figure A.1: Technology stock per thousand worker in 1980 (1995 = 1)



Notes: This figure shows the penetration of the stock of robots, communication technology, information technology and software and databases between 1995-2017 (1995=1) at the aggregated European level.

A.1 Sector aggregation

We consider six sectors as the result of the aggregation and compatibilization between NACE Rev. 1.1 and Rev. 2.[23] 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.

[23]This section relies on the methodology adopted in Petit et al. (2022).

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 sectors used in the analysis. The classification is derived from the NACE classifications such to be compatible across the two versions Rev. 1.1 and Rev. 2. Table A.2 summarizes both NACE classifications in the appendix.

Table A.2: Overview of NACE classifications

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

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

B Additional regressions

Table B.1: Technology exposure between 1995 and 2017 (First stage)

	Linear regression - Dep. var.: technology exposure (EU)			
	2SLS - IV First stage			
	ROB	CT	IT	SDB
Exposure (US)	0.87^{***}	0.14^{**}	0.47^{***}	0.76^{***}
	(0.04)	(0.06)	(0.07)	(0.14)
R^2	0.97	0.98	0.99	0.98
Adj. R^2	0.97	0.98	0.99	0.97
Num. obs.	163	163	163	163

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients of the first-stage regressions for the technology exposure in European regions between 1995 and 2017 which is instrumented with the predicted exposure in the United States over the same period. First-stage regressions are estimated separately for each automation technology with country fixed effects. Each column refer to a technology: robot (ROB), communication technology (CT), information technology (IT), software and database (SDB).

Table B.2: Employment-to-population ratio adjustments to robot exposure during robot investment cycles.

	Dep. var.: % change in the employment-to-population ratio							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-2002 ROB M-wave	−0.14	2.24^{***}	3.44^{***}	3.70^{***}	−0.29	2.13^{***}	3.36^{***}	3.54^{***}
	(0.64)	(0.59)	(0.61)	(0.60)	(0.65)	(0.59)	(0.62)	(0.63)
2002-2006 ROB M-wave	-2.19^{*}	−0.38	−1.13	−1.19	-2.19^{*}	−0.33	−1.09	−1.01
	(1.27)	(1.12)	(1.10)	(1.05)	(1.28)	(1.13)	(1.11)	(1.07)
2006-2013 ROB M-wave	12.07^{***}	9.72^{***}	9.23^{***}	9.47^{***}	12.68^{***}	10.23^{***}	9.71^{***}	10.01^{***}
	(0.90)	(0.81)	(0.79)	(0.76)	(0.92)	(0.83)	(0.81)	(0.78)
2013-2017 ROB M-wave	−0.63	−1.27	-1.43^{*}	-1.64^{**}	−0.72	−1.39	-1.56^{*}	-1.76^{**}
	(0.99)	(0.87)	(0.85)	(0.82)	(1.01)	(0.89)	(0.87)	(0.83)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.42	0.56	0.58	0.63	0.43	0.56	0.58	0.63
Adj. R^2	0.42	0.55	0.57	0.62	0.42	0.56	0.58	0.62
Num. obs.	652	652	652	652	652	652	652	652

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.3: Average wage adjustments to robot exposure during robot investment cycles.

	Dep. var.: % change in average wage							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-2002 ROB M-wave	-6.14^{***}	-5.54^{***}	-5.06^{***}	-5.46^{***}	-6.57^{***}	-6.00^{***}	-5.56^{***}	-5.92^{***}
	(0.80)	(0.83)	(0.89)	(0.87)	(0.81)	(0.84)	(0.89)	(0.88)
2002-2006 ROB M-wave	-6.29^{***}	-5.83^{***}	-6.13^{***}	-6.41^{***}	-6.64^{***}	-6.20^{***}	-6.47^{***}	-6.58^{***}
	(1.56)	(1.57)	(1.58)	(1.49)	(1.58)	(1.58)	(1.59)	(1.49)
2006-2013 ROB M-wave	3.85^{***}	3.25^{***}	3.06^{***}	2.30^{**}	3.96^{***}	3.38^{***}	3.20^{***}	2.16^{**}
	(1.11)	(1.13)	(1.14)	(1.08)	(1.13)	(1.16)	(1.16)	(1.09)
2013-2017 ROB M-wave	1.77	1.61	1.55	1.43	1.62	1.46	1.40	1.20
	(1.22)	(1.22)	(1.22)	(1.15)	(1.25)	(1.24)	(1.24)	(1.16)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.22	0.23	0.23	0.34	0.23	0.24	0.24	0.37
Adj. R^2	0.21	0.22	0.22	0.32	0.22	0.23	0.23	0.35
Num. obs.	651	651	651	651	651	651	651	651

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wage to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.4: Wage share adjustments to robot exposure during robot investment cycles.

	Dep. var.: pp. change in the wage share							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-2002 ROB M-wave	-0.66^{**}	-0.45	-0.21	-0.22	-0.78^{**}	-0.57	-0.35	-0.45
	(0.33)	(0.35)	(0.37)	(0.38)	(0.34)	(0.35)	(0.37)	(0.39)
2002-2006 ROB M-wave	-2.55^{***}	-2.38^{***}	-2.53^{***}	-2.88^{***}	-2.58^{***}	-2.42^{***}	-2.56^{***}	-2.83^{***}
	(0.65)	(0.65)	(0.66)	(0.65)	(0.66)	(0.66)	(0.67)	(0.67)
2006-2013 ROB M-wave	1.30^{***}	1.08^{**}	0.99^{**}	0.97^{**}	1.44^{***}	1.23^{**}	1.13^{**}	1.15^{**}
	(0.46)	(0.47)	(0.47)	(0.47)	(0.48)	(0.49)	(0.49)	(0.49)
2013-2017 ROB M-wave	-0.28	-0.34	-0.37	-0.28	-0.40	-0.46	-0.49	-0.40
	(0.51)	(0.51)	(0.51)	(0.51)	(0.52)	(0.52)	(0.52)	(0.52)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.11	0.12	0.12	0.17	0.11	0.12	0.12	0.17
Adj. R^2	0.10	0.11	0.11	0.14	0.10	0.11	0.11	0.14
Num. obs.	651	651	651	651	651	651	651	651

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in the wage share to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.5: Employment-to-population ratio adjustments to robot exposure during the previous robot investment cycles.

	Dep. var.: % change in the employment-to-population ratio									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2002-2006 ROB M-wave	-3.29	-8.07^{**}	-12.17^{***}	-12.98^{***}	-19.54^{***}	-2.34	-7.55^{*}	-12.04^{***}	-13.01^{***}	-25.67^{***}
	(4.27)	(3.91)	(3.72)	(3.60)	(4.62)	(4.43)	(4.08)	(3.89)	(3.80)	(6.63)
2006-2013 ROB M-wave	14.24^{***}	11.78^{***}	11.04^{***}	11.75^{***}	10.26^{***}	15.40^{***}	12.78^{***}	12.00^{***}	12.64^{***}	11.18^{***}
	(1.04)	(0.97)	(0.92)	(0.85)	(0.76)	(1.07)	(1.01)	(0.96)	(0.89)	(0.88)
2013-2017 ROB M-wave	0.65	0.65	-0.94	-2.71	7.04^{*}	0.89	0.93	-0.74	-2.17	6.30^{*}
	(3.27)	(2.97)	(2.81)	(3.42)	(3.68)	(3.33)	(3.04)	(2.88)	(3.66)	(3.80)
2002-2006 ROB M-wave $w-1$	0.57	3.91^{**}	5.50^{***}	5.89^{***}	10.46^{***}	0.08	3.63^{*}	5.41^{***}	5.82^{***}	14.13^{***}
	(2.16)	(1.99)	(1.89)	(1.84)	(2.40)	(2.24)	(2.07)	(1.97)	(1.93)	(3.47)
2006-2013 ROB M-wave $w-1$	-4.78^{***}	-3.86^{***}	-4.28^{***}	-5.96^{***}	-6.79^{***}	-5.78^{***}	-4.69^{***}	-5.08^{***}	-6.82^{***}	-7.97^{***}
	(1.46)	(1.33)	(1.25)	(1.16)	(0.99)	(1.49)	(1.36)	(1.29)	(1.18)	(1.03)
2013-2017 ROB M-wave $w-1$	-1.20	-1.73	-0.51	0.84	-8.39^{**}	-1.53	-2.10	-0.82	0.15	-6.93^{*}
	(2.97)	(2.70)	(2.55)	(3.13)	(3.37)	(3.04)	(2.77)	(2.62)	(3.36)	(3.61)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.42	0.52	0.58	0.66	0.76	0.44	0.54	0.59	0.67	0.78
Adj. R^2	0.41	0.52	0.57	0.64	0.75	0.43	0.53	0.58	0.65	0.77
Num. obs.	489	489	489	489	489	489	489	489	489	489

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.6: Average wage adjustments to robot exposure during the previous robot investment cycles.

	Dep. var.: % change in average wage									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2002-2006 ROB M-wave	3.40	-2.41	0.04	0.27	-6.06	3.31	-3.19	-0.50	1.98	-2.76
	(4.77)	(4.29)	(4.26)	(4.37)	(5.71)	(5.02)	(4.52)	(4.50)	(4.63)	(8.04)
2006-2013 ROB M-wave	2.94^{**}	-0.06	0.38	0.01	2.67^{***}	3.00^{**}	-0.27	0.20	0.18	3.29^{***}
	(1.16)	(1.07)	(1.06)	(1.04)	(0.95)	(1.21)	(1.12)	(1.11)	(1.08)	(1.07)
2013-2017 ROB M-wave	-0.76	-0.76	0.19	-7.54^{*}	-6.38	-1.38	-1.33	-0.33	-11.01^{**}	-12.81^{***}
	(3.66)	(3.26)	(3.22)	(4.15)	(4.55)	(3.78)	(3.37)	(3.33)	(4.46)	(4.60)
2002-2006 ROB M-wave $w-1$	-5.08^{**}	-1.03	-1.98	-2.12	0.35	-5.20^{**}	-0.76	-1.83	-2.79	-1.02
	(2.41)	(2.18)	(2.16)	(2.23)	(2.97)	(2.54)	(2.30)	(2.28)	(2.36)	(4.21)
2006-2013 ROB M-wave $w-1$	2.01	3.13^{**}	3.39^{**}	3.66^{***}	3.58^{***}	2.04	3.40^{**}	3.63^{**}	3.72^{**}	2.96^{**}
	(1.63)	(1.46)	(1.44)	(1.41)	(1.22)	(1.69)	(1.51)	(1.49)	(1.44)	(1.24)
2013-2017 ROB M-wave $w-1$	2.39	1.75	1.02	8.19^{**}	7.85^{*}	2.83	2.11	1.35	11.44^{***}	14.71^{***}
	(3.32)	(2.96)	(2.92)	(3.80)	(4.17)	(3.44)	(3.07)	(3.03)	(4.10)	(4.38)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.11	0.29	0.32	0.37	0.55	0.11	0.30	0.32	0.39	0.60
Adj. R^2	0.10	0.28	0.30	0.35	0.52	0.10	0.28	0.31	0.37	0.57
Num. obs.	489	489	489	489	489	489	489	489	489	489

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wages to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.7: Wage share adjustments to robot exposure during the previous robot investment cycles.

	Dep. var.: pp. change in the wage share									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2002-2006 ROB M-wave	1.68	0.21	0.03	-0.49	-9.32^{***}	1.26	-0.36	-0.57	-0.88	-23.48^{***}
	(2.06)	(2.00)	(2.02)	(2.09)	(2.98)	(2.16)	(2.11)	(2.13)	(2.24)	(4.02)
2006-2013 ROB M-wave	1.85^{***}	1.10^{**}	1.07^{**}	1.14^{**}	0.73	2.27^{***}	1.46^{***}	1.42^{***}	1.60^{***}	0.48
	(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.52)	(0.52)	(0.53)	(0.52)	(0.54)
2013-2017 ROB M-wave	-0.28	-0.27	-0.35	-0.96	-0.98	-0.25	-0.24	-0.32	-1.48	-7.59^{***}
	(1.58)	(1.52)	(1.53)	(1.99)	(2.38)	(1.62)	(1.57)	(1.57)	(2.16)	(2.30)
2002-2006 ROB M-wave $w-1$	-2.22^{**}	-1.20	-1.12	-1.04	3.82^{**}	-2.00^{*}	-0.90	-0.82	-0.79	11.62^{***}
	(1.04)	(1.02)	(1.03)	(1.07)	(1.55)	(1.09)	(1.07)	(1.08)	(1.14)	(2.11)
2006-2013 ROB M-wave $w-1$	-1.23^{*}	-0.94	-0.96	-1.04	-1.18^{*}	-1.77^{**}	-1.43^{**}	-1.45^{**}	-1.52^{**}	-1.55^{**}
	(0.70)	(0.68)	(0.68)	(0.67)	(0.64)	(0.73)	(0.70)	(0.70)	(0.70)	(0.62)
2013-2017 ROB M-wave $w-1$	-0.00	-0.17	-0.11	0.53	0.77	-0.14	-0.32	-0.26	0.92	7.93^{***}
	(1.43)	(1.38)	(1.38)	(1.82)	(2.17)	(1.48)	(1.43)	(1.43)	(1.99)	(2.19)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.19	0.25	0.25	0.30	0.40	0.20	0.26	0.26	0.30	0.51
Adj. R^2	0.18	0.24	0.24	0.27	0.36	0.19	0.24	0.24	0.28	0.48
Num. obs.	489	489	489	489	489	489	489	489	489	489

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in wage share to the change in robot exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.8: Employment-to-population ratio adjustments to communication technology (CT) exposure during CT investment cycles.

	Dep. var.: % change in the employment-to-population ratio							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 CT M-wave	-1.17^{***}	-1.93^{***}	-1.83^{***}	-1.46^{**}	-1.19^{***}	-1.98^{***}	-1.88^{***}	-0.78
	(0.36)	(0.32)	(0.32)	(0.67)	(0.37)	(0.32)	(0.32)	(0.85)
1998-2001 CT M-wave	0.33	0.47^{*}	0.43^{*}	0.23	0.33	0.48^{*}	0.44^{*}	-0.52
	(0.30)	(0.25)	(0.25)	(0.71)	(0.30)	(0.26)	(0.26)	(0.79)
2001-2006 CT M-wave	-0.48	-0.84^{***}	-0.75^{***}	3.72^{***}	-0.48	-0.86^{***}	-0.76^{***}	3.67^{***}
	(0.30)	(0.26)	(0.26)	(1.27)	(0.31)	(0.27)	(0.27)	(1.40)
2006-2009 CT M-wave	-0.21	0.26	0.33	-0.80	-0.22	0.28	0.35	-0.39
	(0.28)	(0.25)	(0.25)	(0.60)	(0.29)	(0.25)	(0.25)	(1.32)
2009-2013 CT M-wave	1.98^{***}	-5.45^{***}	-5.16^{***}	-4.95^{***}	2.47^{***}	-5.82^{***}	-5.49^{***}	-5.48^{***}
	(0.75)	(0.76)	(0.76)	(1.08)	(0.78)	(0.81)	(0.82)	(1.50)
2013-2017 CT M-wave	-0.18	0.12	0.13	0.05	-0.18	0.13	0.14	0.08
	(0.26)	(0.23)	(0.23)	(0.68)	(0.27)	(0.23)	(0.23)	(0.77)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.23	0.42	0.43	0.52	0.23	0.43	0.43	0.53
Adj. R^2	0.22	0.42	0.42	0.51	0.22	0.42	0.42	0.51
Num. obs.	978	978	978	978	978	978	978	978

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.9: Average wage adjustments to communication technology (CT) exposure during CT investment cycles.

	Dep. var.: % change in average wage							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 CT M-wave	0.38	-0.12	-0.00	1.82*	0.34	-0.18	-0.06	3.30***
	(0.48)	(0.47)	(0.47)	(0.99)	(0.49)	(0.47)	(0.48)	(1.24)
1998-2001 CT M-wave	1.47***	1.57***	1.52***	5.18***	1.51***	1.61***	1.56***	5.73***
	(0.39)	(0.38)	(0.38)	(1.05)	(0.39)	(0.38)	(0.38)	(1.16)
2001-2006 CT M-wave	1.90***	1.66***	1.78***	16.53***	1.90***	1.65***	1.77***	18.65***
	(0.40)	(0.39)	(0.39)	(1.88)	(0.41)	(0.39)	(0.40)	(2.04)
2006-2009 CT M-wave	0.44	0.76**	0.84**	-1.11	0.51	0.85**	0.93**	-5.83^{***}
	(0.38)	(0.37)	(0.37)	(0.89)	(0.38)	(0.37)	(0.37)	(1.93)
2009-2013 CT M-wave	5.28***	0.29	0.65	4.50***	5.68***	0.12	0.53	7.71***
	(0.99)	(1.13)	(1.13)	(1.60)	(1.03)	(1.21)	(1.21)	(2.19)
2013-2017 CT M-wave	0.05	0.25	0.27	-0.48	0.05	0.26	0.27	-0.79
	(0.35)	(0.34)	(0.34)	(1.01)	(0.35)	(0.34)	(0.34)	(1.12)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.11	0.17	0.18	0.32	0.11	0.17	0.18	0.34
Adj. R^2	0.10	0.16	0.17	0.30	0.10	0.16	0.17	0.32
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wage to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.10: Wage share adjustments to communication technology (CT) exposure during investment cycles.

	Dep. var.: pp. change in the wage share							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 CT M-wave	-0.38^{*}	-0.50^{**}	-0.50^{**}	-0.97^{**}	-0.40^{*}	-0.53^{**}	-0.53^{**}	-1.15^{**}
	(0.21)	(0.21)	(0.21)	(0.45)	(0.21)	(0.21)	(0.21)	(0.57)
1998-2001 CT M-wave	0.47^{***}	0.49^{***}	0.49^{***}	1.86^{***}	0.45^{***}	0.48^{***}	0.48^{***}	2.40^{***}
	(0.17)	(0.17)	(0.17)	(0.47)	(0.17)	(0.17)	(0.17)	(0.53)
2001-2006 CT M-wave	-0.15	-0.20	-0.20	5.42^{***}	-0.17	-0.23	-0.23	5.88^{***}
	(0.17)	(0.17)	(0.17)	(0.85)	(0.17)	(0.17)	(0.17)	(0.93)
2006-2009 CT M-wave	0.54^{***}	0.61^{***}	0.61^{***}	0.46	0.56^{***}	0.64^{***}	0.64^{***}	-0.55
	(0.16)	(0.16)	(0.16)	(0.40)	(0.17)	(0.16)	(0.17)	(0.89)
2009-2013 CT M-wave	0.38	-0.74	-0.74	0.62	0.27	-1.08^{**}	-1.08^{**}	-0.07
	(0.42)	(0.50)	(0.50)	(0.72)	(0.44)	(0.53)	(0.53)	(1.00)
2013-2017 CT M-wave	-0.18	-0.14	-0.14	-0.04	-0.19	-0.14	-0.14	-0.18
	(0.15)	(0.15)	(0.15)	(0.46)	(0.15)	(0.15)	(0.15)	(0.52)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.14	0.16	0.16	0.26	0.14	0.16	0.16	0.27
Adj. R^2	0.13	0.15	0.15	0.24	0.13	0.15	0.15	0.25
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in the wage share to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.11: Employment-to-population ratio adjustments to communication technology (CT) exposure during the previous CT investment cycles.

	Dep. var.: % change in the employment-to-population ratio									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 CT M-wave	2.78^{**}	0.82	0.83	-0.96	1.40	4.01^{***}	1.57	1.52	-0.42	5.71^{*}
	(1.41)	(1.19)	(1.19)	(1.68)	(2.40)	(1.51)	(1.27)	(1.28)	(1.97)	(3.38)
2001-2006 CT M-wave	2.33^{*}	0.16	0.21	2.40^{*}	1.73	4.32^{**}	-0.17	-0.46	1.84	-1.39
	(1.29)	(1.08)	(1.10)	(1.30)	(1.61)	(1.79)	(1.52)	(1.59)	(1.65)	(1.86)
2006-2009 CT M-wave	-7.82^{***}	-6.54^{***}	-6.40^{***}	-8.47^{***}	-15.94^{***}	-8.26^{***}	-6.78^{***}	-7.18^{***}	-7.93^{***}	-19.03^{***}
	(2.26)	(1.89)	(1.98)	(2.07)	(2.90)	(2.36)	(1.97)	(2.08)	(2.31)	(3.57)
2009-2013 CT M-wave	2.06^{*}	-8.26^{***}	-8.17^{***}	-8.21^{***}	-9.16^{***}	3.34^{**}	-10.79^{***}	-11.15^{***}	-10.56^{***}	-14.96^{***}
	(1.18)	(1.13)	(1.19)	(1.43)	(1.42)	(1.37)	(1.37)	(1.50)	(1.74)	(1.75)
2013-2017 CT M-wave	-0.15	1.45^{***}	1.45^{***}	1.83^{*}	0.96	-0.31	1.59^{***}	1.62^{***}	1.89^{*}	-0.18
	(0.62)	(0.53)	(0.53)	(0.99)	(1.14)	(0.66)	(0.56)	(0.56)	(1.06)	(1.32)
1998-2001 CT M-wave $w-1$	-3.09^{*}	-0.41	-0.43	2.03	-0.38	-4.64^{**}	-1.34	-1.26	0.67	-3.22
	(1.74)	(1.46)	(1.47)	(2.05)	(2.20)	(1.87)	(1.57)	(1.58)	(2.73)	(3.12)
2001-2006 CT M-wave $w-1$	-2.84^{**}	-1.08	-1.12	0.08	-0.01	-4.71^{***}	-0.75	-0.50	0.02	2.96
	(1.26)	(1.06)	(1.08)	(1.35)	(2.13)	(1.73)	(1.46)	(1.53)	(2.17)	(3.21)
2006-2009 CT M-wave $w-1$	8.11^{***}	7.33^{***}	7.20^{***}	8.17^{***}	15.92^{***}	8.57^{***}	7.65^{***}	8.06^{***}	8.85^{***}	20.98^{***}
	(2.39)	(2.00)	(2.08)	(2.11)	(2.35)	(2.49)	(2.09)	(2.20)	(2.28)	(2.77)
2009-2013 CT M-wave $w-1$	-0.04	0.73^{*}	0.71^{*}	0.59	-1.14	-0.40	1.42^{***}	1.51^{***}	1.95^{***}	0.45
	(0.45)	(0.38)	(0.39)	(0.38)	(1.79)	(0.51)	(0.44)	(0.46)	(0.75)	(1.94)
2013-2017 CT M-wave $w-1$	-0.07	-4.01^{***}	-3.98^{***}	-3.80^{**}	-2.31	0.41	-4.45^{***}	-4.54^{***}	-4.13^{**}	-2.58
	(1.76)	(1.49)	(1.49)	(1.49)	(1.76)	(1.92)	(1.63)	(1.64)	(1.62)	(1.93)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.25	0.48	0.48	0.57	0.61	0.26	0.48	0.48	0.57	0.65
Adj. R^2	0.24	0.47	0.47	0.55	0.59	0.25	0.47	0.47	0.56	0.62
Num. obs.	815	815	815	815	815	815	815	815	815	815

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.12: Average wage adjustments to communication technology (CT) exposure during the previous CT investment cycles.

	Dep. var.: % change in average wage									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 CT M-wave	-0.97	-2.70	-2.64	5.47^{**}	-2.92	-0.52	-2.52	-2.31	6.08^{**}	-10.49^{**}
	(1.85)	(1.72)	(1.73)	(2.49)	(3.54)	(1.94)	(1.83)	(1.83)	(2.83)	(4.90)
2001-2006 CT M-wave	8.60^{***}	6.71^{***}	6.91^{***}	15.16^{***}	12.82^{***}	14.99^{***}	11.33^{***}	12.42^{***}	17.70^{***}	16.51^{***}
	(1.67)	(1.57)	(1.60)	(1.92)	(2.37)	(2.30)	(2.18)	(2.29)	(2.37)	(2.70)
2006-2009 CT M-wave	12.34^{***}	13.46^{***}	13.97^{***}	14.33^{***}	11.97^{***}	13.77^{***}	14.97^{***}	16.48^{***}	11.31^{***}	23.73^{***}
	(2.94)	(2.74)	(2.87)	(3.06)	(4.27)	(3.02)	(2.84)	(2.99)	(3.32)	(5.18)
2009-2013 CT M-wave	9.86^{***}	0.87	1.20	5.60^{***}	7.56^{***}	13.33^{***}	1.84	3.20	6.46^{***}	11.51^{***}
	(1.54)	(1.64)	(1.73)	(2.12)	(2.09)	(1.75)	(1.97)	(2.15)	(2.50)	(2.54)
2013-2017 CT M-wave	2.53^{***}	3.93^{***}	3.90^{***}	5.34^{***}	4.96^{***}	3.17^{***}	4.72^{***}	4.61^{***}	5.86^{***}	4.02^{**}
	(0.81)	(0.76)	(0.76)	(1.46)	(1.67)	(0.84)	(0.80)	(0.81)	(1.53)	(1.91)
1998-2001 CT M-wave $w-1$	3.07	5.44^{**}	5.35^{**}	0.20	4.66	2.55	5.27^{**}	4.95^{**}	0.40	9.20^{**}
	(2.27)	(2.12)	(2.13)	(3.03)	(3.23)	(2.40)	(2.26)	(2.27)	(3.92)	(4.52)
2001-2006 CT M-wave $w-1$	-6.77^{***}	-5.24^{***}	-5.40^{***}	2.11	6.30^{**}	-12.85^{***}	-9.63^{***}	-10.60^{***}	-0.54	3.13
	(1.64)	(1.54)	(1.56)	(2.00)	(3.14)	(2.22)	(2.11)	(2.19)	(3.12)	(4.65)
2006-2009 CT M-wave $w-1$	-12.69^{***}	-13.37^{***}	-13.89^{***}	-16.49^{***}	-19.33^{***}	-14.13^{***}	-14.87^{***}	-16.44^{***}	-20.59^{***}	-28.54^{***}
	(3.11)	(2.89)	(3.02)	(3.13)	(3.47)	(3.20)	(3.00)	(3.16)	(3.28)	(4.01)
2009-2013 CT M-wave $w-1$	-2.27^{***}	-1.60^{***}	-1.68^{***}	-2.09^{***}	-11.59^{***}	-3.48^{***}	-2.00^{***}	-2.34^{***}	-5.92^{***}	-17.93^{***}
	(0.59)	(0.55)	(0.56)	(0.56)	(2.63)	(0.65)	(0.63)	(0.66)	(1.08)	(2.81)
2013-2017 CT M-wave $w-1$	-7.78^{***}	-11.21^{***}	-11.12^{***}	-11.68^{***}	-12.67^{***}	-10.04^{***}	-13.99^{***}	-13.65^{***}	-14.12^{***}	-13.00^{***}
	(2.29)	(2.16)	(2.16)	(2.21)	(2.60)	(2.47)	(2.34)	(2.35)	(2.32)	(2.80)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.19	0.30	0.30	0.40	0.46	0.22	0.31	0.32	0.44	0.52
Adj. R^2	0.17	0.28	0.28	0.37	0.43	0.21	0.30	0.30	0.41	0.49
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wage to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.13: Wage share adjustments to communication technology (CT) exposure during the previous CT investment cycles.

	Dep. var.: pp. change in the wage share									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 CT M-wave	1.59^{**}	1.22	1.23	3.59^{***}	2.31	1.83^{**}	1.35^{*}	1.38^{*}	4.19^{***}	4.64^{**}
	(0.78)	(0.78)	(0.78)	(1.13)	(1.63)	(0.83)	(0.82)	(0.82)	(1.30)	(2.24)
2001-2006 CT M-wave	3.39^{***}	2.99^{***}	3.03^{***}	5.67^{***}	5.37^{***}	6.32^{***}	5.44^{***}	5.61^{***}	7.16^{***}	2.60^{**}
	(0.71)	(0.70)	(0.72)	(0.87)	(1.10)	(0.98)	(0.97)	(1.02)	(1.09)	(1.23)
2006-2009 CT M-wave	1.11	1.35	1.48	2.05	3.90^{**}	1.23	1.52	1.75	1.34	8.44^{***}
	(1.25)	(1.23)	(1.29)	(1.39)	(1.97)	(1.29)	(1.27)	(1.34)	(1.53)	(2.37)
2009-2013 CT M-wave	0.44	-1.47^{**}	-1.39^{*}	0.83	1.25	0.23	-2.52^{***}	-2.31^{**}	-0.18	-1.93^{*}
	(0.65)	(0.74)	(0.78)	(0.96)	(0.97)	(0.75)	(0.88)	(0.96)	(1.15)	(1.16)
2013-2017 CT M-wave	1.94^{***}	2.24^{***}	2.23^{***}	4.10^{***}	3.18^{***}	2.37^{***}	2.74^{***}	2.72^{***}	4.46^{***}	1.51^{*}
	(0.34)	(0.34)	(0.34)	(0.67)	(0.77)	(0.36)	(0.36)	(0.36)	(0.70)	(0.87)
1998-2001 CT M-wave $w-1$	-1.40	-0.90	-0.92	-2.23	-1.23	-1.74^{*}	-1.09	-1.14	-2.54	-3.28
	(0.97)	(0.95)	(0.96)	(1.38)	(1.49)	(1.02)	(1.01)	(1.02)	(1.81)	(2.06)
2001-2006 CT M-wave $w-1$	-3.57^{***}	-3.25^{***}	-3.28^{***}	-0.90	0.12	-6.37^{***}	-5.60^{***}	-5.75^{***}	-3.51^{**}	6.91^{***}
	(0.70)	(0.69)	(0.70)	(0.91)	(1.45)	(0.95)	(0.94)	(0.98)	(1.44)	(2.12)
2006-2009 CT M-wave $w-1$	-0.61	-0.75	-0.88	-1.73	-3.45^{**}	-0.72	-0.90	-1.14	-2.46	-4.73^{***}
	(1.32)	(1.30)	(1.36)	(1.42)	(1.60)	(1.37)	(1.34)	(1.41)	(1.51)	(1.83)
2009-2013 CT M-wave $w-1$	-0.03	0.11	0.10	-0.33	-3.00^{**}	0.02	0.37	0.32	-1.14^{**}	-4.18^{***}
	(0.25)	(0.25)	(0.25)	(0.25)	(1.21)	(0.28)	(0.28)	(0.30)	(0.50)	(1.28)
2013-2017 CT M-wave $w-1$	-6.67^{***}	-7.39^{***}	-7.37^{***}	-8.35^{***}	-7.09^{***}	-8.19^{***}	-9.14^{***}	-9.09^{***}	-9.86^{***}	-5.68^{***}
	(0.98)	(0.97)	(0.97)	(1.01)	(1.20)	(1.05)	(1.05)	(1.05)	(1.07)	(1.28)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.22	0.25	0.25	0.34	0.40	0.25	0.28	0.28	0.37	0.48
Adj. R^2	0.21	0.24	0.24	0.32	0.36	0.24	0.27	0.27	0.35	0.45
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change wage share to the change in CT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.14: Employment-to-population ratio adjustments to information technology (IT) exposure during IT investment cycles.

	Dep. var.: % change in the employment-to-population ratio							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 IT M-wave	-0.93	-0.78	0.33	3.83^{**}	-1.04	-0.89	0.25	4.91^{***}
	(0.99)	(0.84)	(0.83)	(1.52)	(0.99)	(0.85)	(0.83)	(1.80)
1998-2001 IT M-wave	-1.36	0.73	0.25	-1.07	-1.61	0.62	0.11	-3.13^{*}
	(1.15)	(0.99)	(0.96)	(1.68)	(1.18)	(1.01)	(0.99)	(1.89)
2001-2004 IT M-wave	-1.65	-2.01^{**}	-1.39	-0.42	-1.68	-2.04^{**}	-1.41	-0.90
	(1.13)	(0.96)	(0.94)	(1.27)	(1.13)	(0.97)	(0.94)	(1.40)
2004-2007 IT M-wave	0.40	0.22	0.33	0.48	0.42	0.23	0.35	0.69
	(0.45)	(0.39)	(0.38)	(0.46)	(0.46)	(0.39)	(0.38)	(0.48)
2007-2013 IT M-wave	-0.36	-2.61^{***}	-2.92^{***}	-5.00^{***}	-0.38	-2.79^{***}	-3.12^{***}	-6.27^{***}
	(0.42)	(0.37)	(0.36)	(0.66)	(0.43)	(0.39)	(0.38)	(0.98)
2013-2017 IT M-wave	-0.16	-0.19	-0.08	-0.27	-0.17	-0.20	-0.10	-0.27
	(0.32)	(0.27)	(0.26)	(0.53)	(0.32)	(0.27)	(0.26)	(0.57)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.26	0.46	0.49	0.61	0.26	0.46	0.50	0.61
Adj. R^2	0.25	0.46	0.49	0.59	0.25	0.46	0.49	0.60
Num. obs.	978	978	978	978	978	978	978	978

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.15: Average wage adjustments to information technology (IT) exposure during IT investment cycles.

	Dep. var.: % change in average wage							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 IT M-wave	1.66	1.76^{*}	2.41^{**}	8.27^{***}	1.66	1.76	2.41^{**}	12.12^{***}
	(1.11)	(1.07)	(1.08)	(2.09)	(1.12)	(1.07)	(1.08)	(2.46)
1998-2001 IT M-wave	3.83^{***}	5.12^{***}	4.84^{***}	11.44^{***}	4.12^{***}	5.48^{***}	5.18^{***}	13.62^{***}
	(1.30)	(1.25)	(1.25)	(2.32)	(1.33)	(1.29)	(1.28)	(2.58)
2001-2004 IT M-wave	1.02	0.80	1.16	4.97^{***}	1.11	0.90	1.26	7.12^{***}
	(1.27)	(1.22)	(1.22)	(1.75)	(1.28)	(1.23)	(1.22)	(1.92)
2004-2007 IT M-wave	0.63	0.51	0.58	1.04	0.64	0.53	0.60	1.43^{**}
	(0.51)	(0.49)	(0.49)	(0.63)	(0.51)	(0.49)	(0.49)	(0.66)
2007-2013 IT M-wave	2.08^{***}	0.69	0.51	1.81^{**}	2.22^{***}	0.75	0.56	2.70^{**}
	(0.47)	(0.47)	(0.47)	(0.92)	(0.48)	(0.49)	(0.49)	(1.34)
2013-2017 IT M-wave	0.06	0.04	0.10	−0.63	0.07	0.05	0.11	−0.88
	(0.36)	(0.34)	(0.34)	(0.73)	(0.36)	(0.34)	(0.34)	(0.78)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.05	0.13	0.14	0.25	0.05	0.13	0.14	0.27
Adj. R^2	0.04	0.12	0.13	0.23	0.04	0.12	0.13	0.25
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wage to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.16: Wage share adjustments to information technology (IT) exposure during IT investment cycles.

	Dep. var.: pp. change in the wage share							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1998 IT M-wave	0.60	0.64	0.83^{*}	1.39	0.55	0.58	0.78	1.13
	(0.48)	(0.47)	(0.48)	(0.94)	(0.49)	(0.47)	(0.48)	(1.11)
1998-2001 IT M-wave	0.70	1.15^{**}	1.06^{*}	3.13^{***}	0.76	1.25^{**}	1.16^{**}	4.47^{***}
	(0.56)	(0.55)	(0.55)	(1.04)	(0.58)	(0.57)	(0.57)	(1.16)
2001-2004 IT M-wave	0.18	0.10	0.21	1.76^{**}	0.20	0.12	0.23	2.50^{***}
	(0.55)	(0.54)	(0.54)	(0.79)	(0.56)	(0.54)	(0.54)	(0.86)
2004-2007 IT M-wave	0.63^{***}	0.59^{***}	0.61^{***}	1.29^{***}	0.65^{***}	0.61^{***}	0.63^{***}	1.54^{***}
	(0.22)	(0.22)	(0.22)	(0.29)	(0.22)	(0.22)	(0.22)	(0.30)
2007-2013 IT M-wave	0.01	-0.47^{**}	-0.53^{**}	-1.27^{***}	-0.01	-0.53^{**}	-0.59^{***}	-1.72^{***}
	(0.20)	(0.21)	(0.21)	(0.41)	(0.21)	(0.22)	(0.22)	(0.60)
2013-2017 IT M-wave	-0.32^{**}	-0.32^{**}	-0.31^{**}	-0.33	-0.32^{**}	-0.33^{**}	-0.31^{**}	-0.45
	(0.15)	(0.15)	(0.15)	(0.33)	(0.15)	(0.15)	(0.15)	(0.35)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.09	0.13	0.14	0.23	0.09	0.14	0.14	0.25
Adj. R^2	0.08	0.12	0.13	0.21	0.08	0.13	0.13	0.22
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in the wage share to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.17: Employment-to-population ratio adjustments to information technology (IT) exposure during the previous IT investment cycles.

	Dep. var.: % change in the employment-to-population ratio									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 IT M-wave	0.30	3.33	4.01	-1.44	5.47	-0.06	3.95	4.72	-4.16	11.18
	(3.46)	(2.81)	(2.73)	(3.23)	(4.79)	(3.80)	(3.07)	(2.97)	(3.86)	(8.27)
2001-2004 IT M-wave	0.32	-1.44	-0.96	-1.14	2.64	0.35	-1.83	-1.37	-2.47	6.82
	(1.87)	(1.52)	(1.48)	(1.65)	(2.85)	(2.04)	(1.65)	(1.60)	(2.11)	(5.51)
2004-2007 IT M-wave	-0.44	-0.20	0.29	0.40	4.07^{***}	-0.51	-0.21	0.36	-0.06	7.60^{***}
	(1.05)	(0.85)	(0.83)	(1.18)	(1.56)	(1.12)	(0.91)	(0.88)	(1.38)	(2.28)
2007-2013 IT M-wave	-0.12	-4.17^{***}	-4.68^{***}	-6.19^{***}	-3.45^{***}	-0.12	-4.88^{***}	-5.49^{***}	-7.92^{***}	-10.19^{***}
	(0.71)	(0.61)	(0.59)	(1.02)	(1.05)	(0.76)	(0.65)	(0.64)	(1.21)	(1.27)
2013-2017 IT M-wave	-0.29	-0.46	-0.32	-0.28	2.03^{**}	-0.38	-0.57	-0.43	-0.22	3.16^{***}
	(0.46)	(0.37)	(0.36)	(0.53)	(0.95)	(0.47)	(0.38)	(0.37)	(0.58)	(1.00)
1998-2001 IT M-wave $w-1$	-1.51	-1.95	-3.08	0.91	-1.11	-1.38	-2.49	-3.70	1.60	-3.80
	(2.97)	(2.41)	(2.34)	(2.66)	(4.75)	(3.18)	(2.57)	(2.49)	(3.15)	(6.48)
2001-2004 IT M-wave $w-1$	-2.56	-0.85	-0.60	1.09	0.71	-2.59	-0.38	-0.09	2.17	-1.73
	(1.91)	(1.55)	(1.50)	(1.87)	(1.96)	(2.13)	(1.72)	(1.67)	(2.26)	(3.05)
2004-2007 IT M-wave $w-1$	2.33	1.05	0.02	0.12	2.01	2.54	1.11	-0.12	1.70	8.35^{**}
	(2.62)	(2.13)	(2.07)	(2.50)	(3.04)	(2.79)	(2.25)	(2.18)	(3.06)	(3.63)
2007-2013 IT M-wave $w-1$	-0.32	1.45^{**}	1.77^{***}	1.00	0.49	-0.33	1.98^{***}	2.38^{***}	1.52^{*}	4.49^{***}
	(0.77)	(0.63)	(0.62)	(0.66)	(0.63)	(0.81)	(0.66)	(0.64)	(0.80)	(0.77)
2013-2017 IT M-wave $w-1$	0.24	0.49	0.44	-0.32	-4.14^{***}	0.38	0.67	0.62	0.57	-12.16^{***}
	(0.60)	(0.49)	(0.48)	(0.95)	(1.28)	(0.64)	(0.52)	(0.50)	(1.34)	(2.28)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.28	0.53	0.55	0.64	0.70	0.28	0.53	0.56	0.65	0.74
Adj. R^2	0.26	0.52	0.54	0.63	0.68	0.26	0.52	0.55	0.64	0.73
Num. obs.	815	815	815	815	815	815	815	815	815	815

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.18: Average wage adjustments to information technology (IT) exposure during the previous IT investment cycles.

	Dep. var.: % change in average wage									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 IT M-wave	12.05^{***}	14.14^{***}	14.09^{***}	13.79^{***}	-10.93^{*}	14.21^{***}	16.92^{***}	16.87^{***}	18.77^{***}	-35.94^{***}
	(3.84)	(3.57)	(3.58)	(4.38)	(6.38)	(4.19)	(3.91)	(3.91)	(5.10)	(11.11)
2001-2004 IT M-wave	1.30	0.07	0.04	4.34^{*}	0.24	1.49	-0.00	-0.04	6.76^{**}	13.12^{*}
	(2.08)	(1.93)	(1.94)	(2.24)	(3.79)	(2.25)	(2.10)	(2.10)	(2.78)	(7.40)
2004-2007 IT M-wave	2.21^{*}	2.38^{**}	2.35^{**}	3.26^{**}	0.20	2.71^{**}	2.91^{**}	2.87^{**}	3.61^{**}	-0.24
	(1.17)	(1.09)	(1.09)	(1.60)	(2.08)	(1.24)	(1.15)	(1.16)	(1.83)	(3.06)
2007-2013 IT M-wave	4.38^{***}	1.55^{**}	1.58^{**}	6.72^{***}	0.53	5.07^{***}	1.83^{**}	1.87^{**}	7.17^{***}	3.41^{**}
	(0.79)	(0.77)	(0.78)	(1.38)	(1.39)	(0.84)	(0.83)	(0.84)	(1.60)	(1.71)
2013-2017 IT M-wave	0.06	-0.06	-0.07	-0.87	-2.97^{**}	0.17	0.04	0.03	-2.12^{***}	-2.98^{**}
	(0.51)	(0.47)	(0.47)	(0.72)	(1.26)	(0.52)	(0.49)	(0.49)	(0.77)	(1.34)
1998-2001 IT M-wave $w-1$	-7.49^{**}	-7.77^{**}	-7.69^{**}	-0.33	15.08^{**}	-8.94^{**}	-9.67^{***}	-9.59^{***}	-1.88	30.57^{***}
	(3.29)	(3.06)	(3.07)	(3.60)	(6.32)	(3.51)	(3.27)	(3.28)	(4.17)	(8.71)
2001-2004 IT M-wave $w-1$	-0.36	0.84	0.82	-0.58	3.10	-0.47	1.04	1.02	-2.12	-1.59
	(2.11)	(1.97)	(1.97)	(2.54)	(2.60)	(2.35)	(2.19)	(2.20)	(2.99)	(4.10)
2004-2007 IT M-wave $w-1$	-4.41	-5.31^{*}	-5.24^{*}	-5.10	0.29	-5.65^{*}	-6.63^{**}	-6.54^{**}	-4.93	-7.09
	(2.91)	(2.71)	(2.71)	(3.39)	(4.04)	(3.07)	(2.86)	(2.87)	(4.04)	(4.88)
2007-2013 IT M-wave $w-1$	-3.15^{***}	-1.91^{**}	-1.93^{**}	-4.12^{***}	-4.08^{***}	-3.74^{***}	-2.16^{**}	-2.19^{***}	-7.00^{***}	-8.34^{***}
	(0.86)	(0.81)	(0.81)	(0.90)	(0.84)	(0.89)	(0.84)	(0.85)	(1.06)	(1.04)
2013-2017 IT M-wave $w-1$	0.00	0.18	0.18	-2.74^{**}	-0.10	-0.19	0.01	0.01	-8.17^{***}	0.15
	(0.67)	(0.62)	(0.62)	(1.29)	(1.70)	(0.71)	(0.66)	(0.66)	(1.77)	(3.06)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.08	0.20	0.20	0.32	0.44	0.09	0.21	0.21	0.36	0.52
Adj. R^2	0.06	0.19	0.19	0.29	0.41	0.07	0.20	0.20	0.34	0.49
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change average to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.19: Wage share adjustments to information technology (IT) exposure during the previous IT investment cycles.

	Dep. var.: pp. change in the wage share									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1998-2001 IT M-wave	5.14^{***}	5.80^{***}	5.92^{***}	4.95^{**}	1.26	6.28^{***}	7.15^{***}	7.29^{***}	7.30^{***}	3.05
	(1.66)	(1.60)	(1.60)	(1.99)	(3.12)	(1.82)	(1.76)	(1.75)	(2.31)	(5.67)
2001-2004 IT M-wave	1.70^{*}	1.31	1.39	2.32^{**}	-0.04	1.99^{**}	1.51	1.59^{*}	3.54^{***}	4.35
	(0.90)	(0.87)	(0.87)	(1.02)	(1.85)	(0.98)	(0.94)	(0.94)	(1.26)	(3.77)
2004-2007 IT M-wave	0.53	0.58	0.67	2.12^{***}	0.34	0.61	0.68	0.78	2.49^{***}	-0.33
	(0.51)	(0.49)	(0.49)	(0.73)	(1.01)	(0.54)	(0.52)	(0.52)	(0.83)	(1.56)
2007-2013 IT M-wave	0.84^{**}	-0.05	-0.14	-0.71	-0.49	0.86^{**}	-0.19	-0.30	-1.52^{**}	-1.73^{**}
	(0.34)	(0.35)	(0.35)	(0.63)	(0.68)	(0.36)	(0.37)	(0.38)	(0.73)	(0.87)
2013-2017 IT M-wave	0.01	-0.03	-0.00	-0.24	-1.54^{**}	0.08	0.03	0.06	-1.02^{***}	-2.34^{***}
	(0.22)	(0.21)	(0.21)	(0.33)	(0.62)	(0.23)	(0.22)	(0.22)	(0.35)	(0.68)
1998-2001 IT M-wave $w-1$	-4.05^{***}	-4.14^{***}	-4.33^{***}	-1.48	-0.30	-4.89^{***}	-5.12^{***}	-5.34^{***}	-2.09	-0.36
	(1.42)	(1.37)	(1.37)	(1.64)	(3.09)	(1.53)	(1.47)	(1.47)	(1.89)	(4.44)
2001-2004 IT M-wave $w-1$	-1.97^{**}	-1.59^{*}	-1.55^{*}	-1.01	-0.10	-2.28^{**}	-1.79^{*}	-1.74^{*}	-1.67	-2.17
	(0.92)	(0.88)	(0.88)	(1.16)	(1.27)	(1.02)	(0.99)	(0.98)	(1.36)	(2.09)
2004-2007 IT M-wave $w-1$	0.29	0.01	-0.17	-1.96	2.52	0.10	-0.21	-0.43	-2.28	1.33
	(1.26)	(1.21)	(1.21)	(1.54)	(1.98)	(1.34)	(1.29)	(1.29)	(1.83)	(2.49)
2007-2013 IT M-wave $w-1$	-1.14^{***}	-0.75^{**}	-0.70^{*}	-0.52	-0.35	-1.15^{***}	-0.64^{*}	-0.57	-0.38	-0.31
	(0.37)	(0.36)	(0.36)	(0.41)	(0.41)	(0.39)	(0.38)	(0.38)	(0.48)	(0.53)
2013-2017 IT M-wave $w-1$	-0.62^{**}	-0.56^{**}	-0.57^{**}	-3.06^{***}	-1.91^{**}	-0.75^{**}	-0.68^{**}	-0.69^{**}	-6.91^{***}	-6.43^{***}
	(0.29)	(0.28)	(0.28)	(0.59)	(0.83)	(0.31)	(0.30)	(0.30)	(0.80)	(1.56)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.12	0.18	0.19	0.28	0.32	0.12	0.19	0.19	0.33	0.36
Adj. R^2	0.10	0.17	0.17	0.25	0.28	0.11	0.17	0.18	0.31	0.32
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in wage share to the change in IT exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.20: Employment-to-population ratio adjustments to software database (SDB) exposure during SDB investment cycles.

	Dep. var.: % change in the employment-to-population ratio							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1997 SDB M-wave	-0.69^{*}	-1.28^{***}	-1.03^{***}	0.53	-0.79^{**}	-1.43^{***}	-1.17^{***}	0.44
	(0.35)	(0.33)	(0.33)	(0.96)	(0.36)	(0.33)	(0.33)	(1.29)
1997-2000 SDB M-wave	-0.16	-0.28^{**}	-0.25^{*}	-0.25	-0.14	-0.28^{**}	-0.25^{*}	0.16
	(0.15)	(0.13)	(0.13)	(0.44)	(0.15)	(0.14)	(0.13)	(0.52)
2000-2003 SDB M-wave	-0.10	0.24	0.19	1.59^{*}	-0.08	0.29	0.23	3.09^{***}
	(0.24)	(0.23)	(0.22)	(0.88)	(0.25)	(0.23)	(0.23)	(1.10)
2003-2009 SDB M-wave	-0.09^{**}	-0.05	-0.04	-0.20	-0.09^{**}	-0.05	-0.04	-0.78^{***}
	(0.04)	(0.04)	(0.04)	(0.15)	(0.04)	(0.04)	(0.04)	(0.23)
2009-2013 SDB M-wave	0.28^{*}	-0.46^{***}	-0.52^{***}	0.23	0.41^{**}	-0.66^{***}	-0.75^{***}	0.13
	(0.15)	(0.15)	(0.15)	(0.23)	(0.18)	(0.18)	(0.18)	(0.38)
2013-2017 SDB M-wave	-0.08	-0.01	0.01	0.26	-0.09	-0.01	0.01	0.29
	(0.14)	(0.13)	(0.13)	(0.53)	(0.14)	(0.13)	(0.13)	(0.59)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.25	0.37	0.38	0.49	0.25	0.37	0.39	0.49
Adj. R^2	0.24	0.36	0.38	0.47	0.25	0.37	0.38	0.48
Num. obs.	978	978	978	978	978	978	978	978

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.21: Average wage adjustments to software database (SDB) exposure during SDB investment cycles.

	Dep. var.: % change in average wage							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1997 SDB M-wave	0.89^{*}	0.09	0.45	-3.51^{**}	0.88^{*}	0.04	0.41	-6.54^{***}
	(0.51)	(0.48)	(0.48)	(1.45)	(0.52)	(0.49)	(0.49)	(1.95)
1997-2000 SDB M-wave	0.26	0.09	0.13	-2.31^{***}	0.29	0.12	0.16	-3.03^{***}
	(0.21)	(0.20)	(0.20)	(0.67)	(0.21)	(0.20)	(0.20)	(0.78)
2000-2003 SDB M-wave	0.51	0.97^{***}	0.89^{***}	-6.47^{***}	0.58	1.06^{***}	0.99^{***}	-8.97^{***}
	(0.35)	(0.33)	(0.33)	(1.33)	(0.36)	(0.34)	(0.33)	(1.66)
2003-2009 SDB M-wave	0.21^{***}	0.26^{***}	0.28^{***}	0.26	0.21^{***}	0.26^{***}	0.29^{***}	0.42
	(0.06)	(0.06)	(0.05)	(0.22)	(0.06)	(0.06)	(0.05)	(0.34)
2009-2013 SDB M-wave	0.63^{***}	-0.37^{*}	-0.46^{**}	-0.55	0.93^{***}	-0.47^{*}	-0.60^{**}	-1.03^{*}
	(0.22)	(0.22)	(0.22)	(0.34)	(0.26)	(0.26)	(0.26)	(0.57)
2013-2017 SDB M-wave	0.08	0.17	0.20	0.60	0.09	0.18	0.21	0.89
	(0.20)	(0.19)	(0.19)	(0.80)	(0.20)	(0.19)	(0.19)	(0.89)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.07	0.19	0.21	0.30	0.07	0.20	0.22	0.32
Adj. R^2	0.06	0.18	0.20	0.27	0.06	0.19	0.21	0.29
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wage to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.22: Wage share adjustments to software database (SDB) exposure during SDBinvestment cycles.

	Dep. var.: pp. change in the wage share							
	OLS - Baseline				2SLS - IV Second stage			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1995-1997 SDB M-wave	0.26	0.14	0.24	0.81	0.25	0.12	0.22	1.27
	(0.22)	(0.22)	(0.22)	(0.67)	(0.22)	(0.22)	(0.22)	(0.91)
1997-2000 SDB M-wave	-0.18^{**}	-0.21^{**}	-0.19^{**}	-0.50	-0.19^{**}	-0.22^{**}	-0.21^{**}	-0.82^{**}
	(0.09)	(0.09)	(0.09)	(0.31)	(0.09)	(0.09)	(0.09)	(0.36)
2000-2003 SDB M-wave	0.15	0.22	0.20	-1.33^{**}	0.15	0.23	0.21	-2.05^{***}
	(0.15)	(0.15)	(0.15)	(0.62)	(0.15)	(0.15)	(0.15)	(0.78)
2003-2009 SDB M-wave	0.05^{*}	0.06^{**}	0.06^{**}	-0.48^{***}	0.05^{**}	0.06^{**}	0.07^{***}	-0.73^{***}
	(0.03)	(0.03)	(0.03)	(0.10)	(0.03)	(0.03)	(0.03)	(0.16)
2009-2013 SDB M-wave	0.02	-0.12	-0.14	0.10	0.01	-0.20^{*}	-0.24^{**}	0.29
	(0.09)	(0.10)	(0.10)	(0.16)	(0.11)	(0.12)	(0.12)	(0.27)
2013-2017 SDB M-wave	-0.14^{*}	-0.13	-0.12	0.05	-0.14	-0.13	-0.12	0.21
	(0.09)	(0.09)	(0.09)	(0.37)	(0.09)	(0.09)	(0.09)	(0.41)
Final demand		Yes	Yes	Yes		Yes	Yes	Yes
Trade			Yes	Yes			Yes	Yes
Other technologies				Yes				Yes
R^2	0.05	0.06	0.07	0.15	0.05	0.07	0.07	0.15
Adj. R^2	0.04	0.05	0.06	0.12	0.04	0.05	0.06	0.12
Num. obs.	976	976	976	976	976	976	976	976

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in the wage share to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (4) refer to the baseline OLS estimate. Columns (5) to (8) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (6), (3) or (7) and (4) or (8) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), and changes in the other three technologies respectively.

Table B.23: Employment-to-population ratio adjustments to software database (SDB) exposure during the previous SDB investment cycles.

	Dep. var.: % change in the employment-to-population ratio									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997-2000 SDB M-wave	-2.23^{*}	-3.71^{***}	-3.24^{***}	-2.85^{**}	-3.52^{***}	-2.30^{*}	-3.81^{***}	-3.33^{***}	-2.01	-3.65^{**}
	(1.31)	(1.19)	(1.18)	(1.29)	(1.28)	(1.34)	(1.22)	(1.21)	(1.31)	(1.77)
2000-2003 SDB M-wave	4.09^{***}	2.98^{**}	3.25^{**}	3.49^{**}	2.52	4.43^{***}	3.24^{**}	3.53^{**}	4.87^{***}	3.57^{*}
	(1.48)	(1.34)	(1.33)	(1.59)	(1.87)	(1.55)	(1.40)	(1.38)	(1.81)	(2.08)
2003-2009 SDB M-wave	-0.01	0.19^{*}	0.26^{**}	0.48^{**}	-0.68	0.01	0.24^{**}	0.33^{***}	0.04	-1.16^{**}
	(0.12)	(0.11)	(0.11)	(0.24)	(0.47)	(0.13)	(0.12)	(0.12)	(0.33)	(0.53)
2009-2013 SDB M-wave	-0.09	-0.25	-0.26	0.18	1.07^{*}	-0.39	-1.34^{**}	-1.39^{**}	-1.62^{*}	-1.52
	(0.28)	(0.25)	(0.25)	(0.27)	(0.59)	(0.60)	(0.54)	(0.54)	(0.87)	(0.98)
2013-2017 SDB M-wave	-0.09	-0.02	0.01	0.33	0.02	-0.56	-0.64	-0.55	-0.81	-1.89
	(0.28)	(0.26)	(0.25)	(0.56)	(0.73)	(0.60)	(0.55)	(0.54)	(1.00)	(1.37)
1997-2000 SDB M-wave $w-1$	5.01	8.24^{***}	7.18^{**}	5.56^{**}	3.47	5.26	8.55^{***}	7.45^{**}	4.72^{*}	3.82
	(3.16)	(2.86)	(2.84)	(2.74)	(2.82)	(3.25)	(2.94)	(2.91)	(2.86)	(4.15)
2000-2003 SDB M-wave $w-1$	-2.54^{***}	-1.63^{**}	-1.83^{**}	-1.66	-1.61	-2.72^{***}	-1.75^{**}	-1.96^{**}	-1.77	-1.43
	(0.88)	(0.80)	(0.79)	(1.06)	(1.33)	(0.92)	(0.83)	(0.82)	(1.23)	(1.72)
2003-2009 SDB M-wave $w-1$	-0.53	-1.53^{**}	-1.90^{***}	-3.90^{***}	-7.48^{***}	-0.67	-1.85^{***}	-2.29^{***}	-4.42^{***}	-9.34^{***}
	(0.73)	(0.66)	(0.66)	(1.09)	(1.20)	(0.78)	(0.71)	(0.71)	(1.29)	(1.35)
2009-2013 SDB M-wave $w-1$	0.12	-0.11	-0.12^{*}	0.07	-0.65	0.19	0.13	0.12	0.42^{**}	0.31
	(0.08)	(0.07)	(0.07)	(0.08)	(0.47)	(0.14)	(0.13)	(0.12)	(0.17)	(0.52)
2013-2017 SDB M-wave $w-1$	0.00	0.03	0.01	-0.09	0.08	0.61	0.82	0.72	1.54	2.52^{**}
	(0.30)	(0.27)	(0.27)	(0.27)	(0.28)	(0.76)	(0.68)	(0.67)	(1.12)	(1.13)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.28	0.41	0.42	0.52	0.58	0.28	0.41	0.43	0.53	0.62
Adj. R^2	0.26	0.40	0.41	0.50	0.56	0.27	0.40	0.42	0.51	0.60
Num. obs.	815	815	815	815	815	815	815	815	815	815

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in employment-to-population ratio to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

Table B.24: Average wage adjustments to software database (SDB) exposure during the previous investment cycles.

	Dep. var.: % change in average wage									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997-2000 SDB M-wave	10.09^{***}	8.16^{***}	8.88^{***}	6.57^{***}	9.01^{***}	8.85^{***}	6.95^{***}	7.68^{***}	4.27^{**}	9.90^{***}
	(1.90)	(1.76)	(1.75)	(1.97)	(1.92)	(1.95)	(1.81)	(1.79)	(1.99)	(2.67)
2000-2003 SDB M-wave	0.01	-1.44	-1.03	-6.74^{***}	-9.93^{***}	0.90	-0.61	-0.19	-8.18^{***}	-11.11^{***}
	(2.14)	(1.98)	(1.96)	(2.42)	(2.80)	(2.24)	(2.08)	(2.06)	(2.75)	(3.14)
2003-2009 SDB M-wave	0.13	0.39^{**}	0.50^{***}	0.98^{***}	1.34^{*}	0.09	0.38^{**}	0.50^{***}	1.49^{***}	1.27
	(0.18)	(0.16)	(0.16)	(0.37)	(0.70)	(0.19)	(0.18)	(0.18)	(0.50)	(0.80)
2009-2013 SDB M-wave	0.33	0.11	0.10	0.00	-4.14^{***}	2.42^{***}	1.21	1.15	2.98^{**}	-0.20
	(0.40)	(0.37)	(0.37)	(0.41)	(0.88)	(0.87)	(0.81)	(0.80)	(1.33)	(1.48)
2013-2017 SDB M-wave	-0.02	0.07	0.11	0.46	-0.59	0.30	0.20	0.34	2.53^{*}	2.48
	(0.41)	(0.38)	(0.37)	(0.86)	(1.09)	(0.88)	(0.81)	(0.80)	(1.52)	(2.07)
1997-2000 SDB M-wave $w-1$	-23.76^{***}	-19.56^{***}	-21.19^{***}	-20.35^{***}	-25.19^{***}	-20.83^{***}	-16.69^{***}	-18.34^{***}	-17.93^{***}	-27.76^{***}
	(4.57)	(4.23)	(4.19)	(4.18)	(4.22)	(4.71)	(4.38)	(4.34)	(4.36)	(6.28)
2000-2003 SDB M-wave $w-1$	0.30	1.50	1.20	0.08	2.36	-0.19	1.04	0.73	-0.96	0.01
	(1.28)	(1.19)	(1.17)	(1.61)	(1.99)	(1.33)	(1.24)	(1.23)	(1.87)	(2.60)
2003-2009 SDB M-wave $w-1$	0.52	-0.78	-1.35	-4.04^{**}	-0.79	0.83	-0.67	-1.33	-5.57^{***}	-0.79
	(1.05)	(0.98)	(0.97)	(1.67)	(1.79)	(1.14)	(1.06)	(1.06)	(1.97)	(2.04)
2009-2013 SDB M-wave $w-1$	0.10	-0.21^{**}	-0.23^{**}	-0.36^{***}	3.62^{***}	-0.36^{*}	-0.45^{**}	-0.46^{**}	-0.90^{***}	3.29^{***}
	(0.11)	(0.10)	(0.10)	(0.12)	(0.70)	(0.20)	(0.19)	(0.18)	(0.26)	(0.79)
2013-2017 SDB M-wave $w-1$	0.12	0.15	0.12	0.07	0.11	-0.28	-0.01	-0.15	-2.43	-1.37
	(0.44)	(0.40)	(0.40)	(0.41)	(0.42)	(1.10)	(1.02)	(1.00)	(1.70)	(1.72)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.10	0.24	0.26	0.34	0.45	0.10	0.23	0.25	0.35	0.49
Adj. R^2	0.09	0.22	0.24	0.31	0.41	0.09	0.22	0.24	0.33	0.46
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the log change in average wages to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

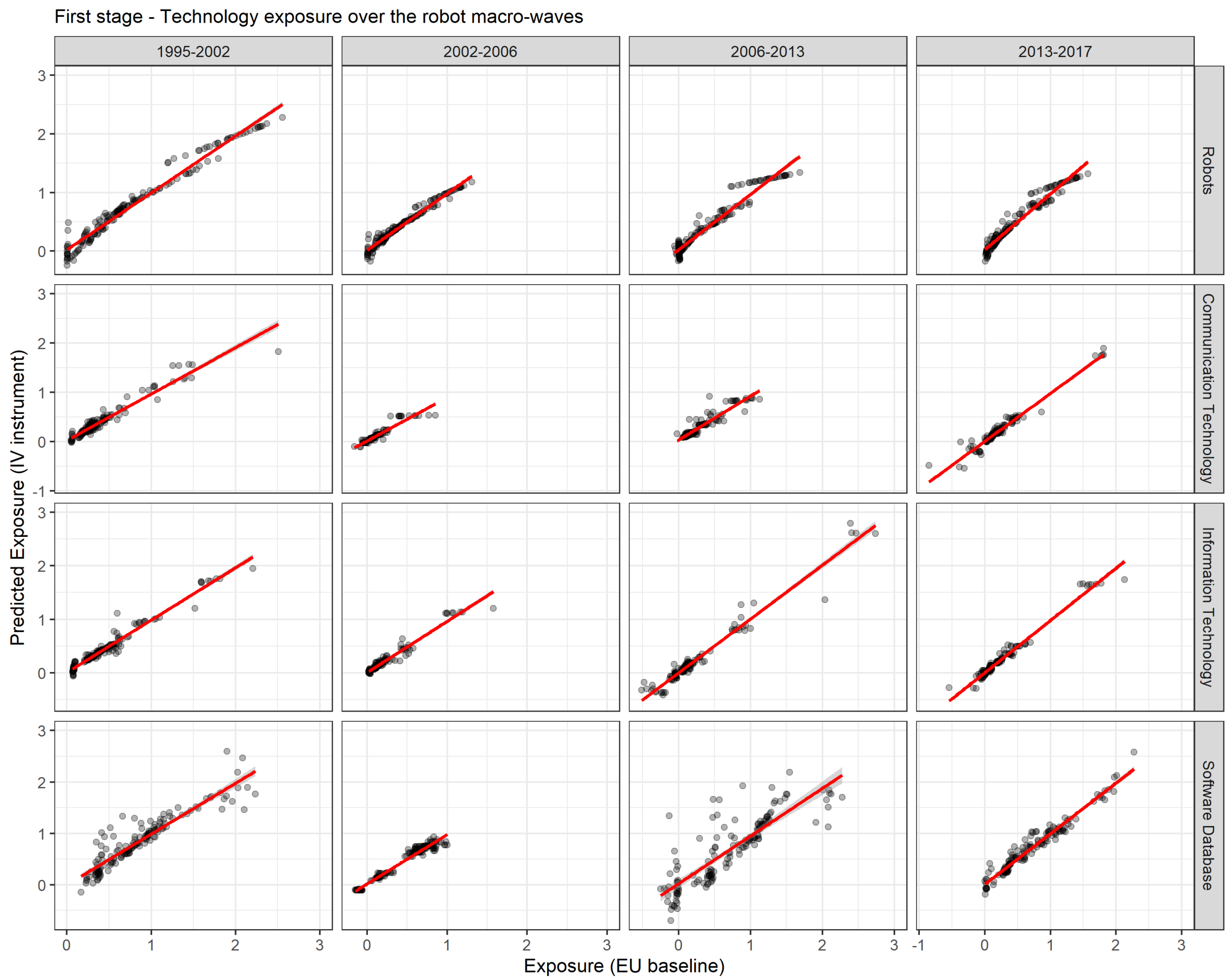
Table B.25: Wage share adjustments to software database (SDB) exposure during the previous SDB investment cycles.

	Dep. var.: pp. change in the wage share									
	OLS - Baseline					2SLS - IV Second stage				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
1997-2000 SDB M-wave	1.13	0.95	1.22	1.71^{*}	2.15^{**}	1.36	1.18	1.45^{*}	1.55^{*}	2.57^{**}
	(0.81)	(0.81)	(0.81)	(0.92)	(0.92)	(0.83)	(0.83)	(0.82)	(0.93)	(1.29)
2000-2003 SDB M-wave	−0.48	−0.61	−0.46	−1.19	−1.62	−0.63	−0.78	−0.62	−2.01	-2.55^{*}
	(0.92)	(0.91)	(0.91)	(1.14)	(1.34)	(0.95)	(0.95)	(0.94)	(1.29)	(1.51)
2003-2009 SDB M-wave	−0.10	−0.07	−0.03	-0.43^{**}	-0.57^{*}	-0.17^{**}	-0.14^{*}	−0.10	-0.73^{***}	-0.94^{**}
	(0.07)	(0.08)	(0.08)	(0.17)	(0.33)	(0.08)	(0.08)	(0.08)	(0.24)	(0.39)
2009-2013 SDB M-wave	−0.09	−0.11	−0.12	0.11	−0.63	−0.56	-0.68^{*}	-0.70^{*}	0.65	−0.39
	(0.17)	(0.17)	(0.17)	(0.19)	(0.42)	(0.37)	(0.37)	(0.37)	(0.62)	(0.71)
2013-2017 SDB M-wave	−0.21	−0.20	−0.18	−0.02	−0.81	0.38	0.37	0.42	2.45^{***}	3.21^{***}
	(0.17)	(0.17)	(0.17)	(0.40)	(0.52)	(0.37)	(0.37)	(0.37)	(0.71)	(1.00)
1997-2000 SDB M-wave $w-1$	−3.16	−2.78	-3.38^{*}	-4.54^{**}	-6.20^{***}	-3.78^{*}	-3.39^{*}	-4.00^{**}	-5.10^{**}	-7.04^{**}
	(1.95)	(1.95)	(1.94)	(1.96)	(2.02)	(2.00)	(2.00)	(1.99)	(2.04)	(3.03)
2000-2003 SDB M-wave $w-1$	0.38	0.49	0.38	−0.08	0.09	0.47	0.59	0.48	0.01	−0.21
	(0.55)	(0.55)	(0.54)	(0.76)	(0.95)	(0.57)	(0.57)	(0.56)	(0.88)	(1.25)
2003-2009 SDB M-wave $w-1$	0.94^{**}	0.82^{*}	0.61	−0.24	1.18	1.42^{***}	1.28^{***}	1.04^{**}	0.12	1.55
	(0.45)	(0.45)	(0.45)	(0.78)	(0.86)	(0.48)	(0.48)	(0.48)	(0.92)	(0.98)
2009-2013 SDB M-wave $w-1$	0.04	0.01	0.00	−0.06	0.74^{**}	0.14	0.13	0.13	−0.13	1.16^{***}
	(0.05)	(0.05)	(0.05)	(0.06)	(0.34)	(0.09)	(0.09)	(0.08)	(0.12)	(0.38)
2013-2017 SDB M-wave $w-1$	0.08	0.08	0.07	0.02	0.30	−0.67	−0.65	−0.70	-3.22^{***}	-2.55^{***}
	(0.19)	(0.19)	(0.18)	(0.19)	(0.20)	(0.47)	(0.46)	(0.46)	(0.80)	(0.83)
Final demand		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Trade			Yes	Yes	Yes			Yes	Yes	Yes
Other technologies				Yes	Yes				Yes	Yes
Other technologies (Lag)					Yes					Yes
R^2	0.06	0.07	0.08	0.16	0.27	0.07	0.08	0.09	0.19	0.32
Adj. R^2	0.04	0.05	0.06	0.13	0.23	0.06	0.06	0.08	0.15	0.28
Num. obs.	814	814	814	814	814	814	814	814	814	814

Notes: $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$. Standard errors between parentheses. This table summarizes the coefficients from the estimated linear regressions of adjustments of the change in the wage share to the change in SDB exposure in European regions during investment cycles in this technology. Technology exposure is constructed as a shift-share. Columns (1) to (5) refer to the baseline OLS estimate. Columns (6) to (10) refer to the second stage of the 2SLS IV estimate for which technology exposures are instrumented separately using the predicted exposure in the US. Columns (2) or (7), (3) or (8), (4) or (9), (5) or (10) include control variables which are changes in final domestic demand (measured with the real consumption index), changes in trade exposure (measured with imports from China), changes in the other three technologies in w, changes in the other three technologies in $w-1$ respectively.

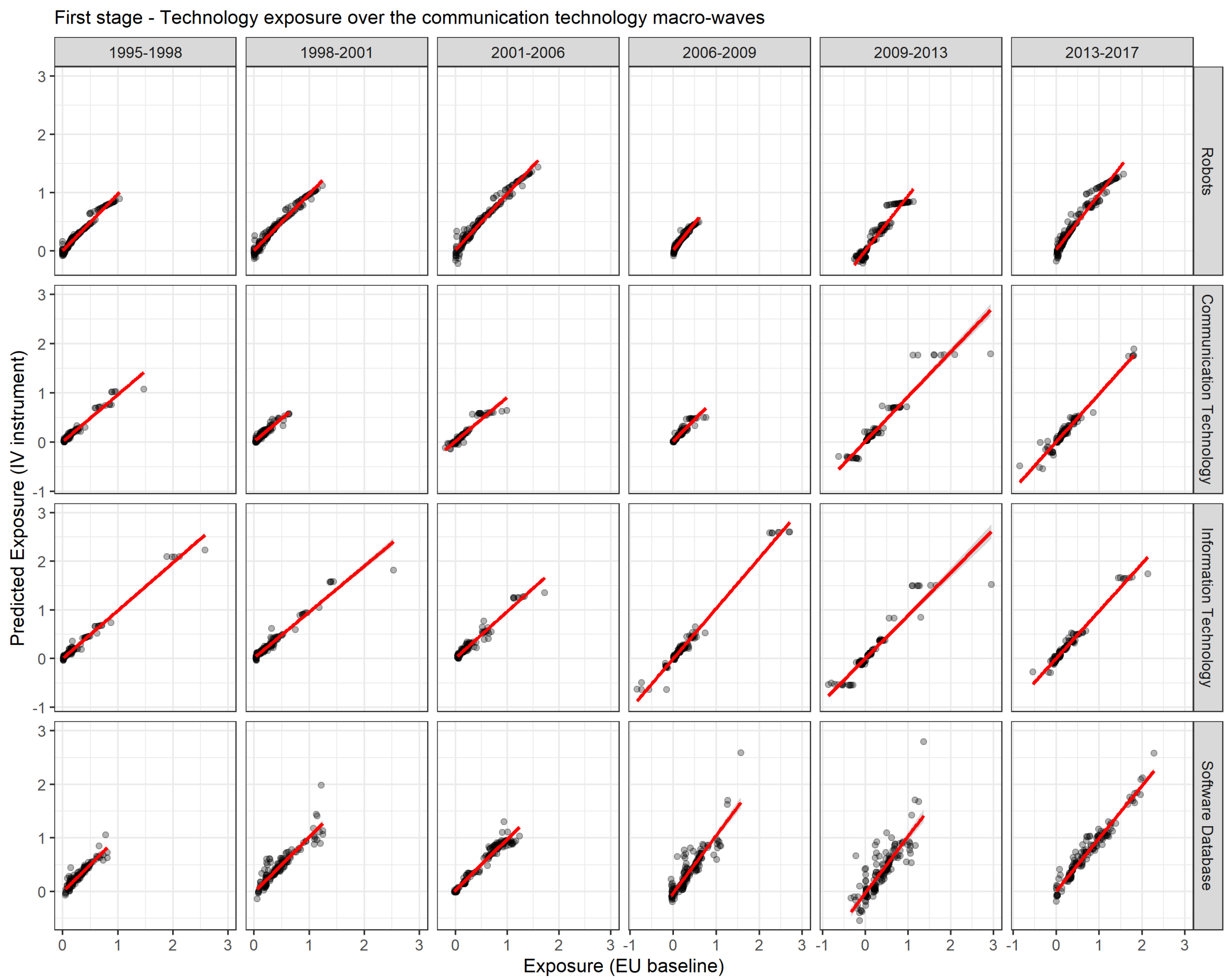
C Additional figures

Figure C.1: Technology exposure during robot investment cycles (First stage)



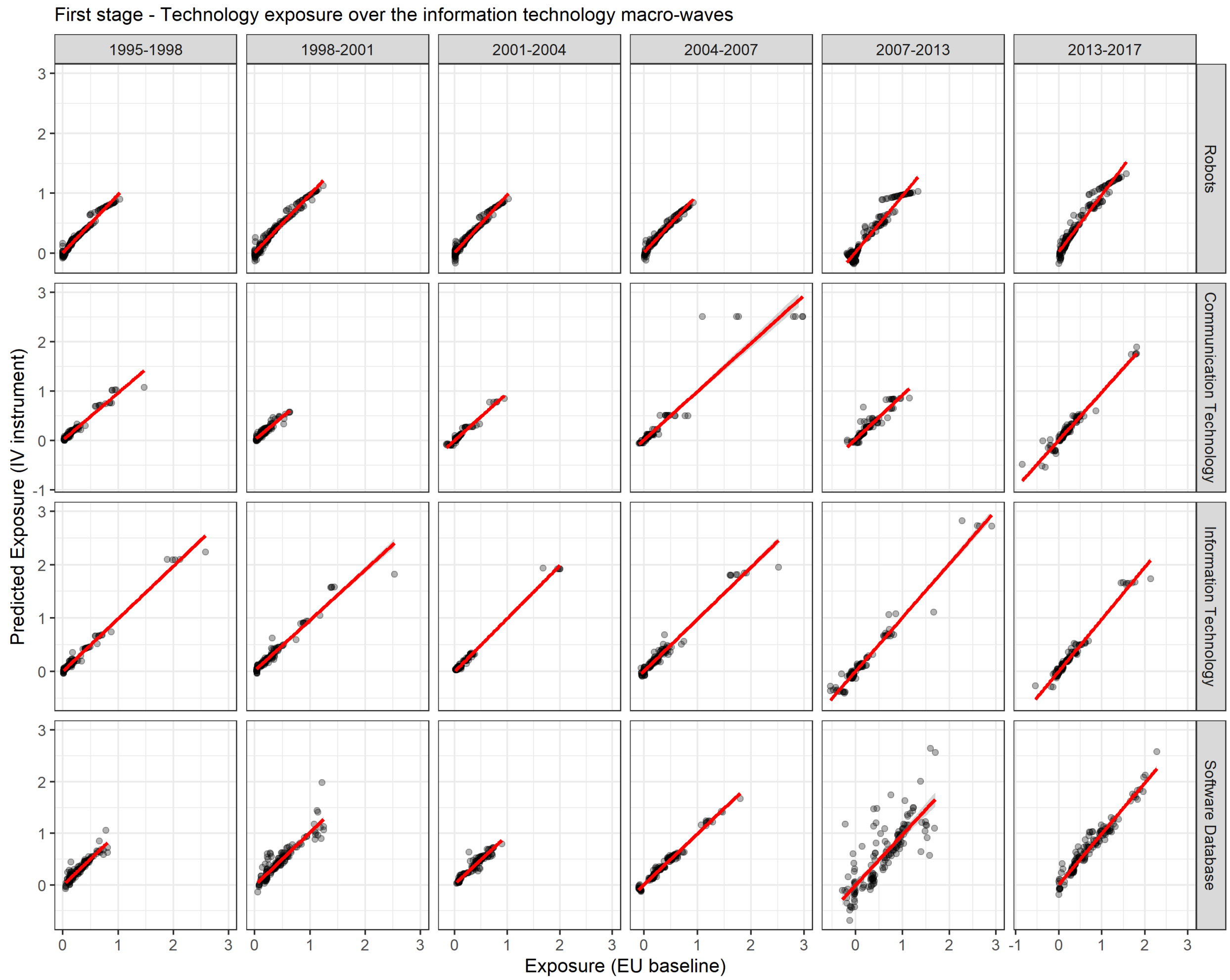
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by robot investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with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

Figure C.2: Technology exposure during communication technology investment cycles (First stage)



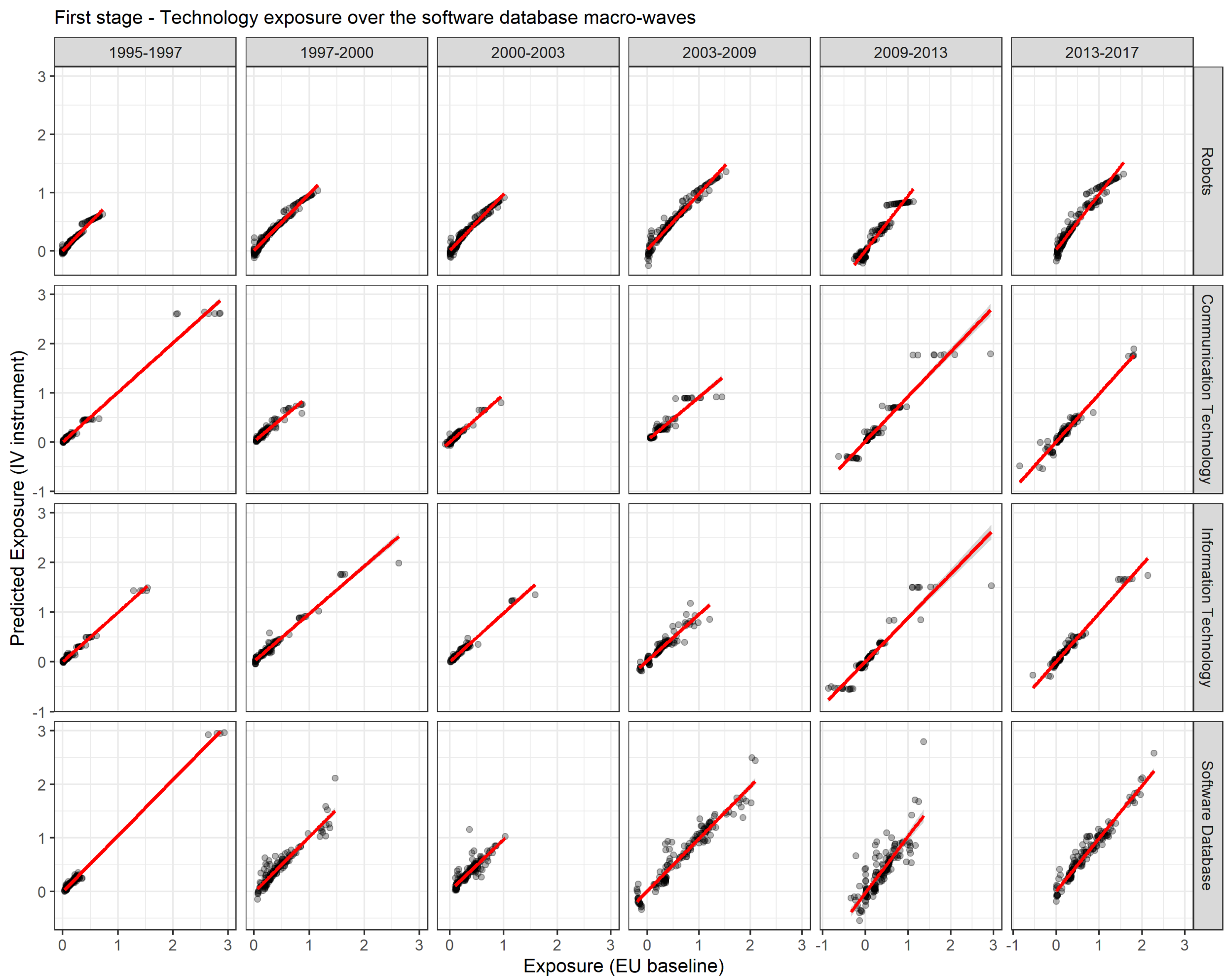
Notes: This figure presents the first-stage regressions for the technology exposure in European regions by CT investment cycles (x-axis) instrumented with the predicted exposure in the United States over the same period (y-axis). First-stage regressions are estimated separately for each cycle with country-fixed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

Figure C.3: Technology exposure during information technology investment cycles (First stage)



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

Figure C.4: Technology exposure during software database investment cycles (First stage)



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