THE ECONOMY 2030 INQUIRY
SHAPING A DECADE OF CHANGE

Adopt, adapt and improve

A brief look at the interplay between labour markets and technological change in the UK

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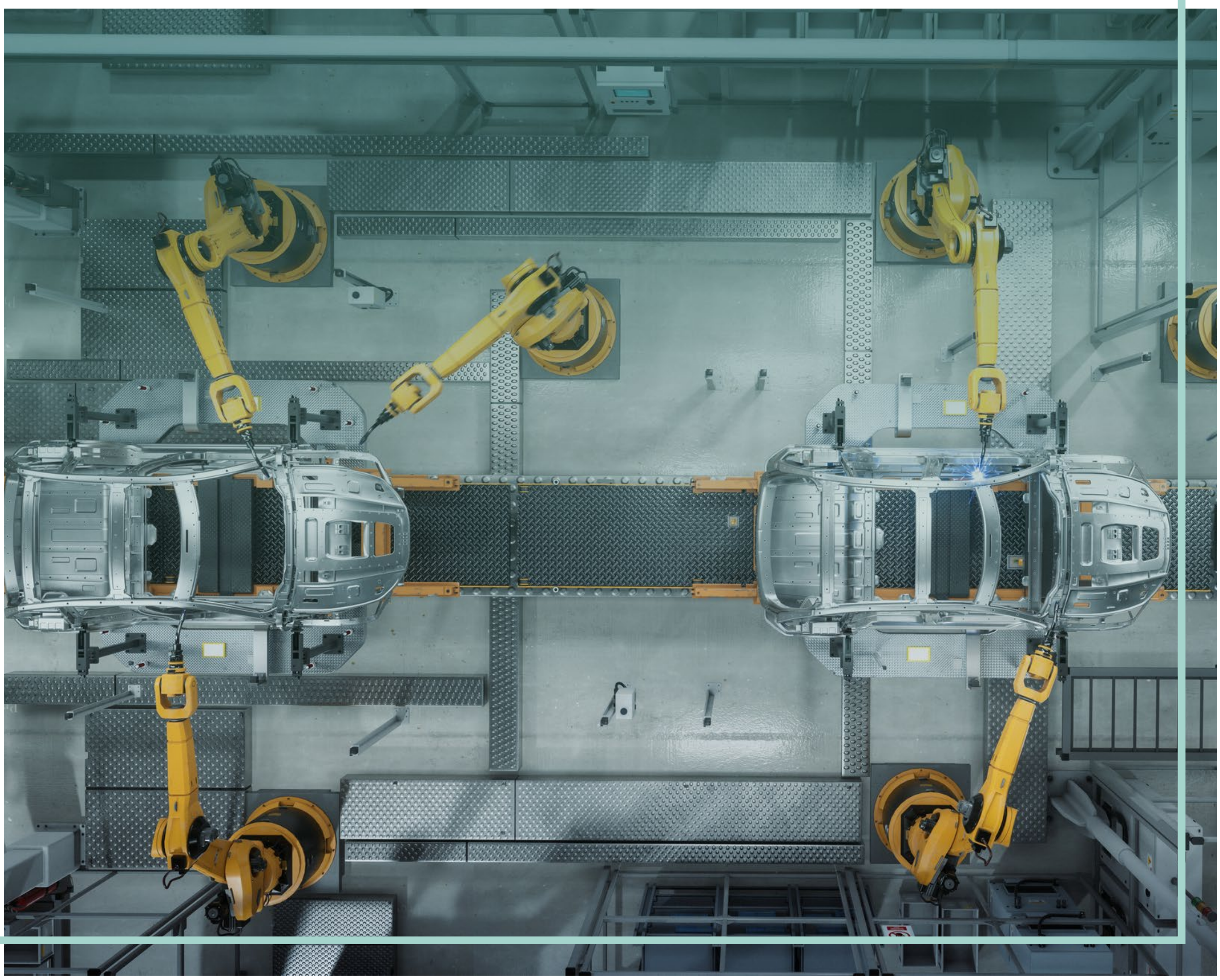
November 2022



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The Economy 2030 Inquiry is a collaboration between the Resolution Foundation and the Centre for Economic Performance at the London School of Economics, funded by the Nuffield Foundation. The Inquiry's subject matter is the nature, scale, and context for the economic change facing the UK during the 2020s. Its goal is not just to describe the change that Covid-19, Brexit, the Net Zero transition and technology will bring, but to help the country and its policy makers better understand and navigate it against a backdrop of low productivity and high inequality. To achieve these aims the Inquiry is leading a two-year national conversation on the future of the UK economy, bridging rigorous research, public involvement and concrete proposals. The work of the Inquiry will be brought together in a final report in 2023 that will set out a renewed economic strategy for the UK to enable the country to successfully navigate the decade ahead, with proposals to drive strong, sustainable and equitable growth, and significant improvements to people's living standards and well-being.

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Summary

Worries that jobs will be lost to automation are not new, but have been heightened since the release of Frey and Osborne's 2013 study, which warned that nearly half of jobs in the US were at 'high risk' of automation.[1] Nearly a decade on, this short briefing note looks at both the current and longer-term picture of the relationship between technology and jobs and pay.

We now know that the period since the Frey & Osborne study has been one of rising rather than falling employment. In the four decades from the 1970s to the 2000s the UK's working age employment rate tended to peak at around 73 per cent; on the eve of the Covid pandemic it reached 76 per cent. It's also the case that even some of the jobs considered by Frey & Osborne to be at highest risk of automation, such as car washers and kitchen assistants, have grown fast in this period. Alongside high employment, productivity and real wages have stagnated. On the face of it, this is not a picture which fits well with concerns about the loss of jobs to technology.

But of course – job destruction was only ever half of the story (even if that was the half that the commentary around Frey and Osborne's paper focused on). Automation doesn't just destroy jobs, it can also raise demand for other workers, and create the space for entirely new jobs. Consistent with this, we have evidence that exposure to automation has affected the cross-section of employment growth in the UK – both in the last decade but also in the longer-term. This is consistent with what is now a wide body of international evidence pointing to the importance of automation for wage determination. So automation is affecting jobs. But the fact that aggregate employment continues to grow alongside these effects suggests automation's job-destroying impact continues to be offset by positive indirect effects.

Overall, while we must remain vigilant to the impact of automation, especially since it affects some people and places more than others, the most pressing problems facing the UK economy are not too much automation, but low investment and low productivity growth. We should worry more about these and less about robots taking our jobs.

Frey and Osborne's 2013 warnings of large numbers of jobs 'at risk' triggered fresh concern about automation

The fear that many jobs will be lost to automation has become ever more present in the policy and public discourse. Partly this comes from fast developments in Artificial Intelligence (AI) technologies. But we can also link it to work of Carl Frey and Michael Osborne, who in 2013 published a paper arguing that 47 per cent of jobs in the US were

1 C Frey & M Osborne, 'The Future of Employment: How susceptible are jobs to computerisation?', September 2013.

at risk of computerisation in the next 20 years.[2] Their follow up paper applying the same methods to the UK predicted that 35 per cent of jobs were at risk.[3]

It's important to note at the outset that interpretation of their predictions have tended to be incomplete, focusing only on the employment-reducing effects of new technology. As we discuss below, new technology can also have indirect positive effects. But still, given it's been almost 10 years since the Frey & Osborne paper (roughly half way through the 20-year timeline they used to assess jobs' risk of automation), can we learn anything from what has happened in this period?

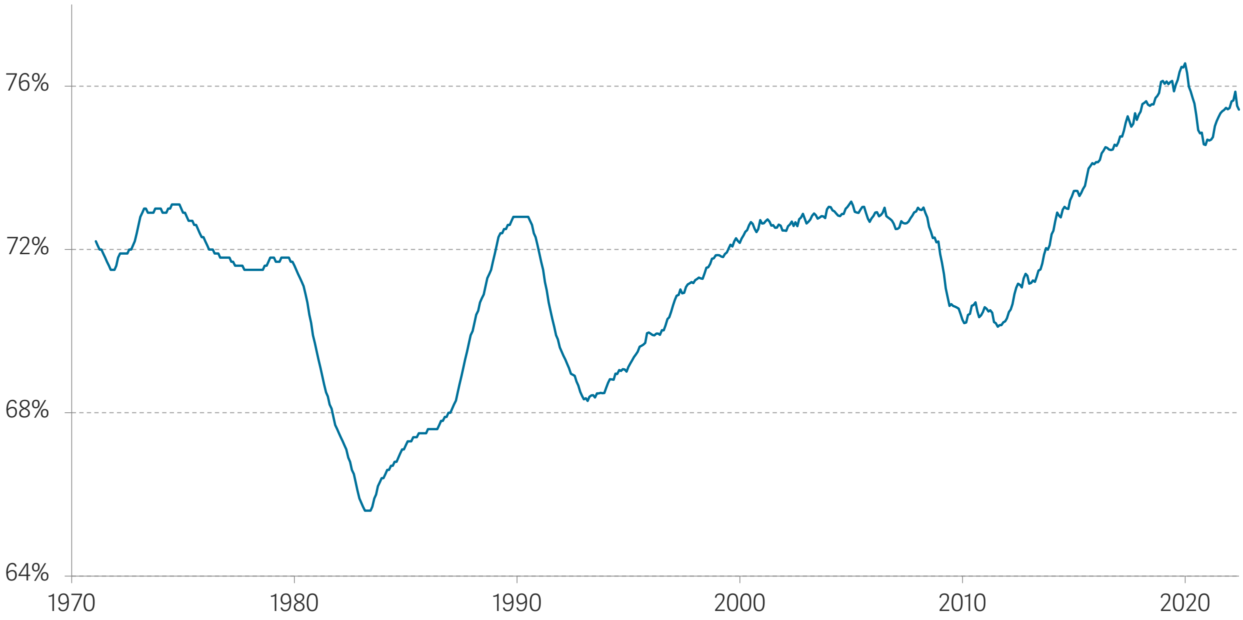
There are two observations we can make. First, and most obviously, it has been a period of rising employment (see Figure 1.). From 2013 the working age employment rate rose every year until the Covid pandemic, reaching a high of 76.3 per cent in early 2020. In previous decades, the employment rate tended to peak at around 73 per cent.[4] So in aggregate, the amount of work being done is more than resisting any downward pressure from technology.

Secondly, employment has also grown in some of the occupations which were considered to be at greatest risk of automation. In Figure 2 we show employment growth from 2013 to 2019 for the occupations which, according to automobility probabilities produced by ONS and OECD based on the Frey and Osborne study, were at highest and lowest risk of automation. There is some vindication for Frey and Osborne; generally speaking the occupations with low risk (in blue – including doctors and teachers) have seen stronger employment growth than the occupations with highest risk of automation (the occupations in red – including farm drivers or shelf fillers). But there are important exemptions to this pattern. Some 'high risk' occupations have seen strong employment growth – including car washers, leisure attendants and kitchen assistants. This should tell us that automation risk is hard to assess, or that there are other factors besides technology which shape demand for different jobs. And it should prompt us to reflect on how we should interpret studies which involve predictions of automation risk, and in general how the discussion about the economic effects of technological change should be conducted.

2 C Frey & M Osborne, 'The Future of Employment: How susceptible are jobs to computerisation?', September 2013.
3 C Frey & M Osborne, 'The Future of Employment: How susceptible are jobs to computerisation?', September 2013.
4 Rising employment Is not unique to the UK. The 15-64 employment rate across the OECD was also around three percentage points higher In 2019 than In 2013. Source: OECD (2022), Employment rate (indicator). doi: 10.1787/1de68a9b-en (Accessed on 30 September 2022).

FIGURE 1: **Employment reached new highs in the post-financial crisis era**

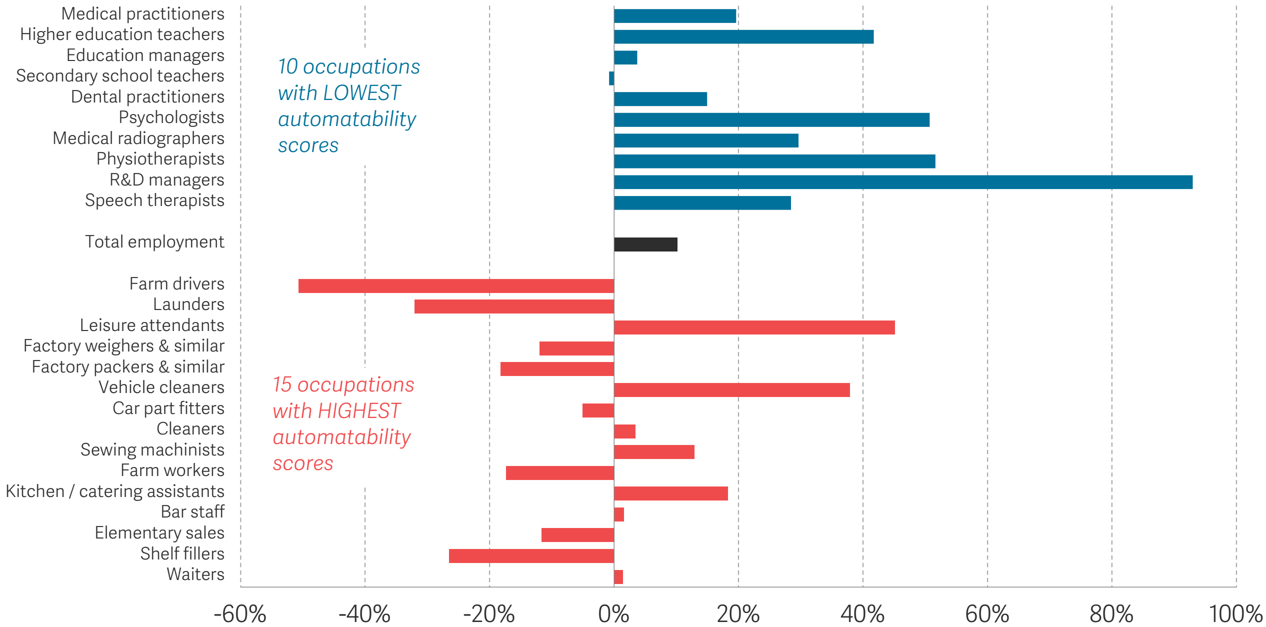
16-64 employment rate: UK



SOURCE: ONS, Labour Force Survey.

FIGURE 2: **Some occupations considered by Frey/Osborne to have the highest risk of automation have grown in size since their work**

Change in employment, 2013-2019, by occupations with highest and lowest automatability scores according to ONS based on Frey/Osborne: UK



NOTES: Occupations ordered by automatability score: lowest (top) to highest (bottom). Scores are taken from ONS database, which maps Frey/Osborne automatability scores to UK occupations.
SOURCE: Employment data from analysis of LFS, ONS. Automatability scores are from ONS, derived from Frey/Osborne, published in the article: ONS, Which occupations are at highest risk of being automated?, July 2019.

There is more to automation than job destruction – the effects of technological change on the labour market are complex and often opposing

Right from the start, the idea of automation contained both its negative effects, but also countervailing positive effects. Keynes described 'technological unemployment' as 'unemployment due to our discovery of means of economising the use of labour outrunning the pace at which we can find new uses for labour'.[5] This 'race' between labour-saving technology and new uses/tasks for workers has always been the basis for economic thinking regarding the consequences of technological adoption for jobs and wages.[6]

Most recently the focus of the discussion regarding the employment effects of technological change has focused on automation - a type of labour-saving technology with the potential to reduce the demand for workers that specialise in certain tasks. To understand the effects of automation technologies we need to go beyond the headline-grabbing negative effect known as 'substitution' or 'displacement', whereby new technologies directly replace labour in the production of a certain good because they are cheaper. There is also a 'productivity' effect – the fact that automation reduces the cost of the goods produced implies an increase in demand for those (now more affordable) goods which, in turn, increases demand for non-automated workers. The combination of the two effects suggests the net effects are ambiguous. And it implies the existence of winners and losers as result of automation, with demand potentially depressed for some workers (those performing automated tasks) and rising for others (those able to do non-automated tasks). Notice that this pattern of winners and losers finds echoes in the recent studies of the effects of globalization and international trade.[7]

Another less discussed consequence of technological adoption that has recently gained traction in the economic debate is that of labour 'augmentation' or 'reinstatement'.[8] This is the idea that new technologies can in practice create new demand for labour through the creation of new tasks (or 'uses' in Keynes' words) for workers to perform. The effect relies on the premise that technology developers innovate in a way that is complementary to labour or capital according to their relative abundance (and hence prices), and that therefore if labour is plentiful and wages are low relative to the price

5 J Keynes, 'Economic Possibilities for our Grandchildren', 1931.
6 For discussion of the evolution of the economic literature on the topic see: D Autor, 'The labor market Impacts of technological change: from unbridled enthusiasm to qualified optimism to vast uncertainty', July 2022.
7 For a review of the literature Into effects of International trade In labour markets see: D Autor, D Dorn & G Hanson, 'The China Shock: Learning from Labor-Market Adjustment to Large Changes in Trade', January 2016; and J MacLaren 'Globalization and Labor Market Dynamics', August 2017.
8 For more detail on economic models that purpose the reinstatement/augmentation effect please see D Acemoglu & P Restrepo, 'The Race between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment', June 2018; and D Autor, A Salomons & B Seegmiller, 'New Frontiers: The Origins and Content of New Work, 1940–2018', August 2022, for a detailed discussion.

of capital, innovators have an incentive to create technologies that make use of labour. Such technologies increase demand for workers and eventually raise their pay.

The combined result of the opposing effects on employment and wages of workers described above is therefore ambiguous. Moreover, the effect can be different at the firm or sector level than at the aggregate level. For example, one might find that automation has positive effects on employment and wages for a firm adopting automation technology while also having a negative effect in the wider industry in which that firm operates due to strengthened product competition.[9] Equally, within a firm or industry, one might see certain workers losing their jobs and/or experiencing downward pressure on pay while workers performing tasks more complementary to the technology adopted gain in terms of pay and employment.[10]

Lower paid workers compete with robots, middle earners face competition from software, while higher earners are likely to see artificial intelligence doing some of their tasks

Having argued that the effects of technology are ambiguous, we now move on to setting out what has happened in practice. We look at data spanning the last four decades, and set out how at the level of different occupations and places the adoption of and exposure to automation has shaped the UK labour market.

Before discussing the results of the occupational analysis, it is important to note that, unlike other studies, the measures of exposure used are based on past technological advancements (as measured by the number of registered patents) and are therefore not meant to capture emerging technologies still in early development. Furthermore, these measures have been constructed with the goal of capturing mostly patterns of automation that imply a significant level of substitution between workers and technologies. The analysis reflects potential displacement gradients rather than the productivity and reinstatement effects that these same technologies have brought for several industries and labour markets – many of which have been consistently documented.[11] Box 1 provides more detail on how we measure exposure to technology.

9 For a discussion about the difference In effects of automation at firm, product market and Industry level please see P Aghion, C Antonin, S Bunel & X Jaravel, 'The Effects of Automation on Labor Demand: A Survey of the Recent Literature', February 2022.
10 See W Dauth, S Findeisen, J Suedekum and N Woessner, 'The Adjustment of Labor Markets to Robots', May 2021.
11 The following studies are examples of evidence of consistent productivity and/or reinstatement effects of technological change: G Graetz & G Michaels, 'Robots at work' , December 2018; D Acemoglu & P Restrepo, 'Automation and New Tasks: How Technology Displaces and Reinstates Labor', Spring 2019, D Autor, A Salomons & B Seegmiller, 'New Frontiers: The Origins and Content of New Work, 1940–2018', August 2022; and P Aghion, C Antonin, S Bunel & X Jaravel, 'Modern Manufacturing Capital, Labor Demand, and Product Market Dynamics: Evidence from France', December 2021.

BOX 1: How we measure exposure to technology

A common practice when studying the impacts of technological change on the structure of employment is to think of occupations as bundles of tasks that workers need to perform. Considering the composition and degree of exposure to automation of the tasks that characterize an occupation, one can construct measures of how susceptible a given occupation is to new technologies. The way occupational exposure measures have been built in the past include the use of occupational descriptions combined with subjective understanding of how certain technologies[12], the training of machine learning algorithms based on an expert assessment of exposure in a sample of occupations[13] and the use of natural language processing algorithms combining occupation descriptors and technological patent texts.

For the occupational analysis in this report, we will be using a measure of exposure to technology developed by Michael Webb which falls within the last category previously described.[14] He uses textual analysis algorithms to match patent text and occupation descriptions in order to identify the degree to which tasks performed in a given occupation can be automated by new technologies. Intuitively, the more tasks in an occupation that can be automated by technologies made available through patents the higher the exposure of that occupation to certain technologies. Hence, the process of construction of exposure scores aims at measuring task-substitution patterns rather than other labour-augmenting effects that the same technologies can have in the same or different occupations. After mapping the exposure measures to the occupation classification used in the UK, one can study how employment and pay dynamics have evolved in the UK for less or more exposed occupations.[15]

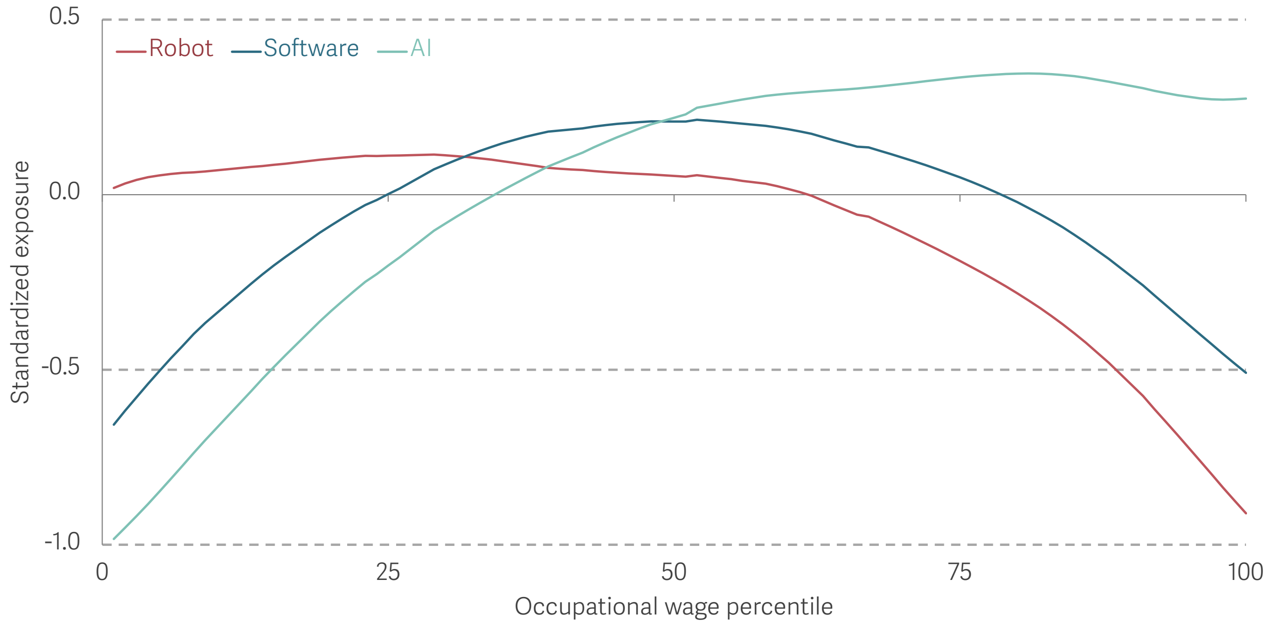
Figure 3 starts by showing how different measures of exposure to automation are distributed across the wage distribution set at the beginning of the period of analysis. Although the standardized exposure scores do not have a straightforward cardinal interpretation, a higher score means that jobs in a given percentile of the wage distribution is more likely to be automated by a certain technology. A clear

12 For examples see D Autor, F Levy, & R Murnane, 'The skill content of recent technological change: An empirical exploration', November 2003; D Acemoglu & D Autor, 'Skills, Tasks and Technologies: Implications for Employment and Earnings', 2011; D Autor & D Dorn, 'The growth of low-skill service jobs and the polarization of the US labor market', December 2021.
13 For examples see C Frey & M Osborne, 'The Future of Employment: How susceptible are jobs to computerisation?', September 2013; J Manyika et al, 'A future that works: automation, employment and productivity', November 2017; and E Brynjolfsson, T Mitchell, & D Rock 'What can machines learn, and what does it mean for occupations and the economy?' , May 2018.
14 M Webb, 'The Impact of Artificial Intelligence on the Labor Market' , January 2020.
15 See the Appendix for the details of the crosswalk procedure.

pattern emerges when looking at the exposure to different technologies across pay percentiles: workers in lower paid occupations have historically been more exposed to robot advancements, those in the middle of the pay distribution have seen software innovations being able to perform part of their tasks and higher earners may start to see some of their work being automated by AI. Note that this pattern is very much in line with that shown for the US by Michael Webb – implying that the ranking of occupational pay is strongly aligned between the two countries. Furthermore, the differential exposure along the wage distribution to the various technologies aligns with previous explanations of the effects of technological change on labour markets: the process of polarization due to ICT technologies (software)[16] affecting middle skilled workers or the manufacturing sector exposure to automated robot adoption[17] where most of the workers are relatively low skilled.

FIGURE 3: **Exposure to technology across the wage distribution varies by type of technology**

Standardized exposure to different types of technology by occupational wage percentile



NOTES: Average of employment weighted standardized occupation-level exposure scores for robots, software and AI crosswalked from Webb (2020) by occupational wage percentile rank in 1981 using a locally weighted smoothing regression.
SOURCE: CEP analysis of LFS, ASHE and Michael Webb (2020)

16 Examples of studies of polarization In the UK, US and Germany are as follows: M Goos & A Manning, 'Lousy and lovely jobs: the rising polarization of work in Britain', February 2007; D Autor & D Dorn, 'The growth of low-skill service jobs and the polarization of the US labor market', August 2013; and A Spitz Oener, 'Technical Change, Job Tasks, and Rising Educational Demands: Looking outside the Wage Structure', April 2006.

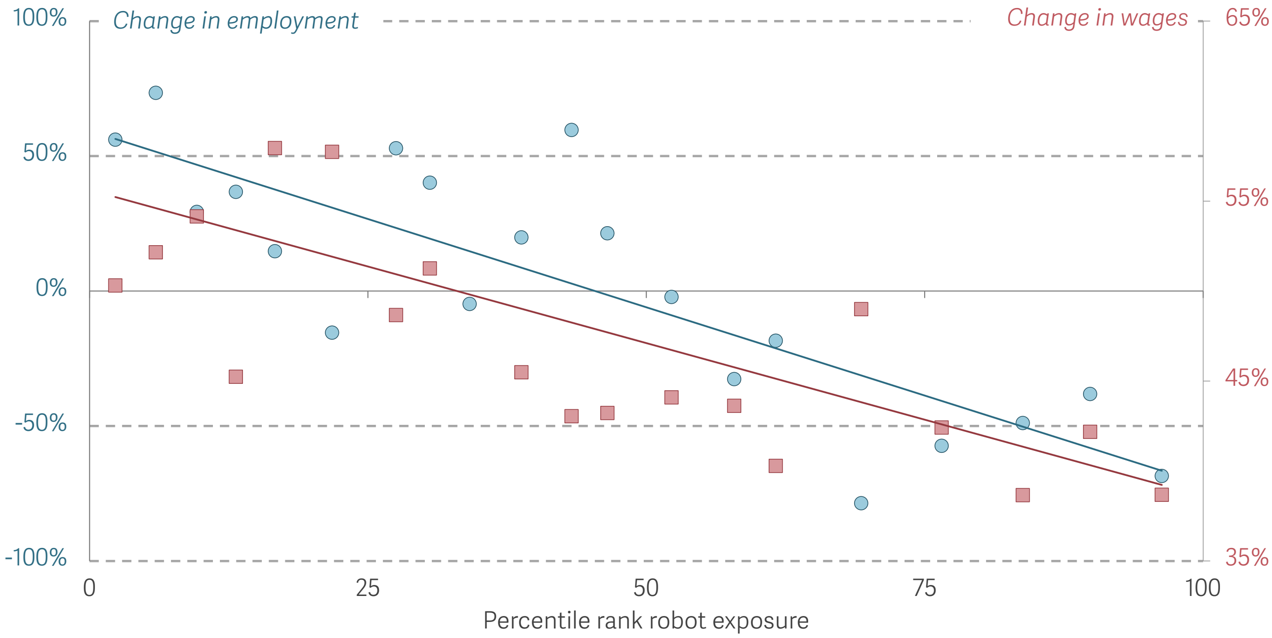
17 The following studies find lower skilled workers are most affected by robot adoption: G Graetz & G Michaels, 'Robots at work', December 2018; D Acemoglu & P Restrepo, 'Robots and jobs: Evidence from US labor markets', June 2020; and W Dauth, S Findeisen, J Suedekum & N Woessner, 'The Adjustment of Labor Markets to Robots', December 2021.

Higher robot exposure has been associated with worse employment and wage performance

Having established how different technologies show potential for automation across occupational pay, we next explore how actual employment and wages trajectories relate to the degree of exposure on each measure. Figure 4 displays the long-run relationship between the growth in employment and wages by the degree of exposure to robot technologies.

FIGURE 4: **Over 40 years employment and wages have seen slower growth for occupations highly exposed to robot technologies**

Changes in employment and wage growth between 1981 and 2019 by percentiles of robot exposure



NOTES: Binscatter plot of change in employment measured as DHS change of each occupation share of employment between 1981 and 2019 and the change in wages measured as DHS change in each occupation mean full-time weekly wage. Percentile rank of robot exposure is calculated as the employment weighted percentiles of the corresponding exposure score according to the 1981 employment occupational structure.
SOURCE: CEP analysis of LFS, ASHE and Michael Webb (2020)

As mentioned previously, the cardinality of the exposure scores does not lend itself to a meaningful economic interpretation, however when these scores are translated into employment weighted percentiles their ordinal rank offers useful insights. The employment weighted exposure rank shows us that a worker in the 95th percentile of robot rank exposure has 5 per cent of workers working in occupations with a higher susceptibility of having their tasks automated by robot advancements. During the period 1981 to 2019 there was a significant negative relationship between employment and real gross weekly wage growth and the ranking of exposure to robots in the UK labour market.[18] It is important to note that relative employment losses have, however, been concentrated mostly at the highest deciles (above the 60th percentile)[19] of exposure and that real wages have still grown, even if slower, for workers at those levels of exposure. Examples of highly exposed occupations which have seen both absolute and relative employment losses are metal plate workers, moulders, and crane drivers, each of which has seen a sizeable portion of their job content automated by robotic technologies.

Workers exposed to software technologies have experienced slower employment growth but the same pattern is harder to establish for wages

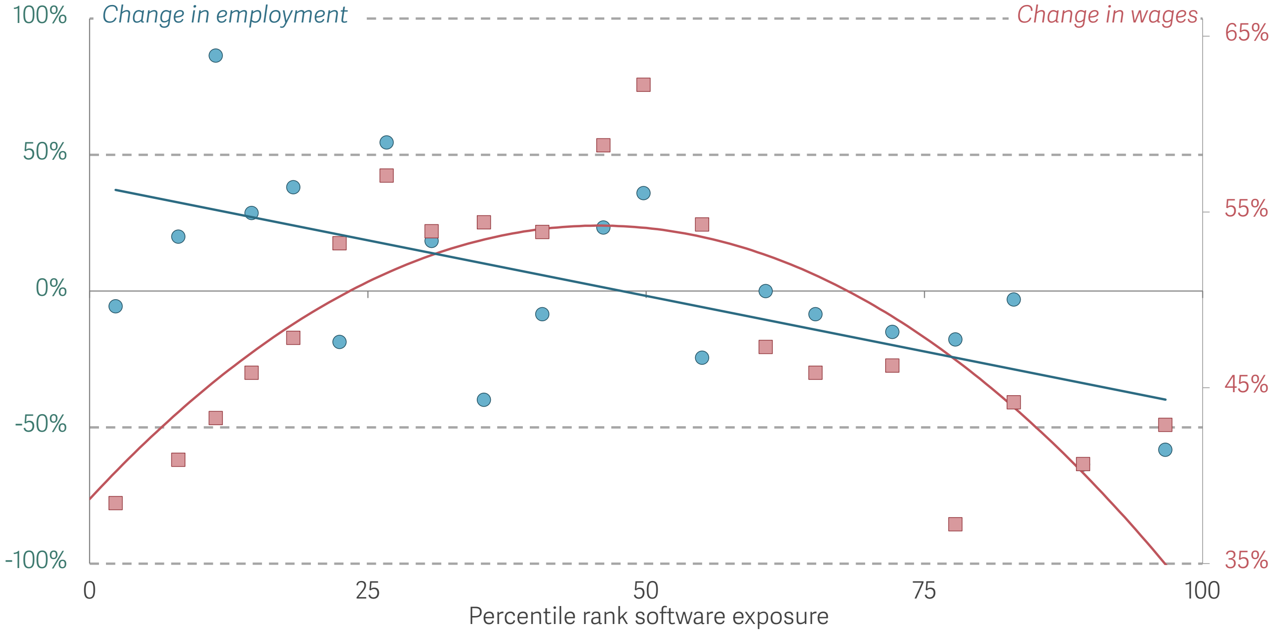
Similar to workers exposed to robotic advancements, individuals working in occupations highly exposed to software technologies have seen a slower employment growth over the last 4 decades, as shown in Figure 5. Energy plant operators and printers were among the occupations most exposed that have seen their employment shrink over this period, whereas higher education teachers and senior care workers who perform tasks harder to automate by software (including social face-to-face interactions) have seen their share of employment grow significantly expressing the higher demand for workers with non-automatable skills.[20]

Although employment changes and software exposed seem to tell a story consistent with substitution between technology and workers, the relation with respect to wage growth is less clear. As presented in Figure 5, the association between wage growth and technological exposure through software is better described as a reverse U-shape – with both occupations at the lowest and highest percentiles experiencing relatively slower pay growth and middle ranked occupation seeing a stronger performance in terms of their wages. The lack of a consistently negative correlation between wage growth and software exposure in the UK is consistent with polarization studies conducted on the adoption of ICT technologies in this same setting.[21]

18 These results are robust to controlling for other demand factors. See Appendix for estimates
19 Absolute employment losses, falling total employment counts, are further concentrated in the top of the exposure distribution (80th percentile and above).
20 The regression coefficient Is robust to controlling for further demand factors and compositional changes. See Appendix for estimates.
21 The following studies do not find strong evidence for wage polarization In the UK: M Goos & A Manning, 'Lousy and lovely jobs: the rising polarization of work in Britain', February 2007; D Oesch, 'Occupational Change in Europe: How Technology and Education Transform the Job Structure', September 2013; and A Salvatori, 'The anatomy of job polarisation in the UK', June 2018.

FIGURE 5: **Although employment growth has been negative related to software technology exposure, the relation with wages has been less clear**

Changes in employment and wage growth between 1981 and 2019 by percentiles of software exposure



NOTES: Binscatter plot of change in employment measured as DHS change of each occupation share of employment between 1981 and 2019 and the change in wages measured as DHS change in each occupation mean full-time weekly wage. Percentile rank of software exposure is calculated as the employment weighted percentiles of the corresponding exposure score according to the 1981 employment occupational structure.
SOURCE: CEP analysis of LFS, ASHE and Michael Webb (2020)

It is too early to assess the effects of AI exposure

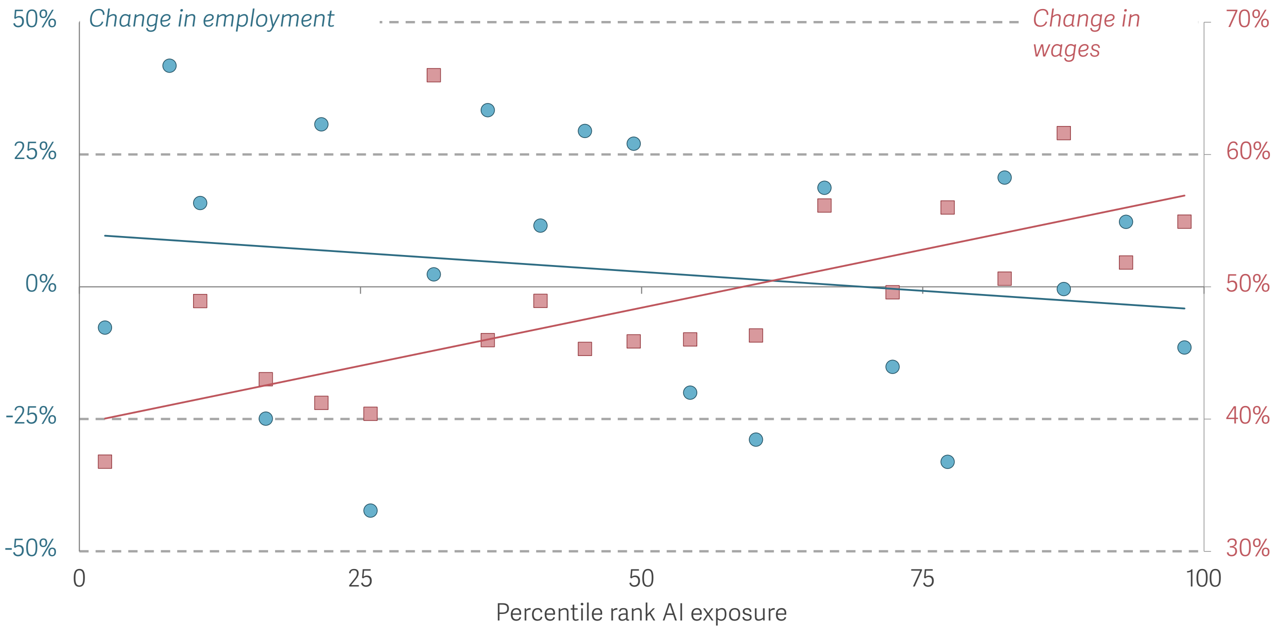
The final technology we analyse in this section is AI. Advancements in AI have been relatively recent and most are still in development, and we have not yet have seen widespread implementation in contrast with the first two technologies discussed. Considering the timing of adoption and the long period of analysis, it is perhaps not surprising that Figure 6 shows no meaningful relation between higher exposure to AI and employment changes between 1981 and 2019.[22] Furthermore, the positive link found between more highly exposed workers and their wage growth can have different explanations. On one hand, we may argue that the AI technology available so far is complementing and enhancing the productivity of workers most exposed to it; on the other hand, considering the time window used in the analysis this relation may be conflicting the exposure to AI technologies with a well-established increasing demand for highly skilled workers which are more likely to be exposed to AI.[23] As concluded in

22 Although the slope of the regression line Is negative, It Is statistically Insignificant and not robust to control for industry specific demand shits. See Appendix for estimates.
23 Indeed, we find that after controlling for the skill composition of the occupations the coefficient estimates halves Its magnitude despite remaining statistically significant.

several studies concerning the recent impacts of AI on workers' labour market prospects, it is too early to make a consistent assessment of what are (and will be) the effects of AI technologies particularly on the aggregate of the economy and labour markets.[24]

FIGURE 6: **The association between employment growth and AI exposure is weak while the positive association with wage growth may indicate complementarity**

Changes in employment and wage growth between 1981 and 2019 by percentiles of AI exposure



NOTES: Binscatter plot of change in employment measured as DHS change of each occupation share of employment between 1981 and 2019 and the change in wages measured as DHS change in each occupation mean full-time weekly wage. Percentile rank of AI exposure is calculated as the employment weighted percentiles of the corresponding exposure score according to the 1981 employment occupational structure.
SOURCE: CEP analysis of LFS, ASHE and Michael Webb (2020)

Going from national to regional – technology adoption assessed through actual robot installations

Although the previous analysis presents an interesting opportunity to look at how, at the national level, employment and pay growth dynamics have interplayed with technological exposure, it struggles to establish a causal relationship. Moreover, to some, the measure of exposure used can feel 'intangible' due to its complex construction using patents and occupational descriptions. With that in mind, several recent studies have tried to assess the effects of actual robot installations on jobs and wages. This measure of technology adoption is arguably more 'direct' as it measures yearly purchases and installations of robots in each industry by country. In the following section, we conduct a short UK-

24 See Felten, E W., M Raj, & R Seamans, 'A Method to Link Advances in Artificial Intelligence to Occupational Abilities', May 2018; D Acemoglu, D Autor, J Hazell, & P Restrepo, 'Artificial Intelligence and Jobs: Evidence from Online Vacancies', April 2022.

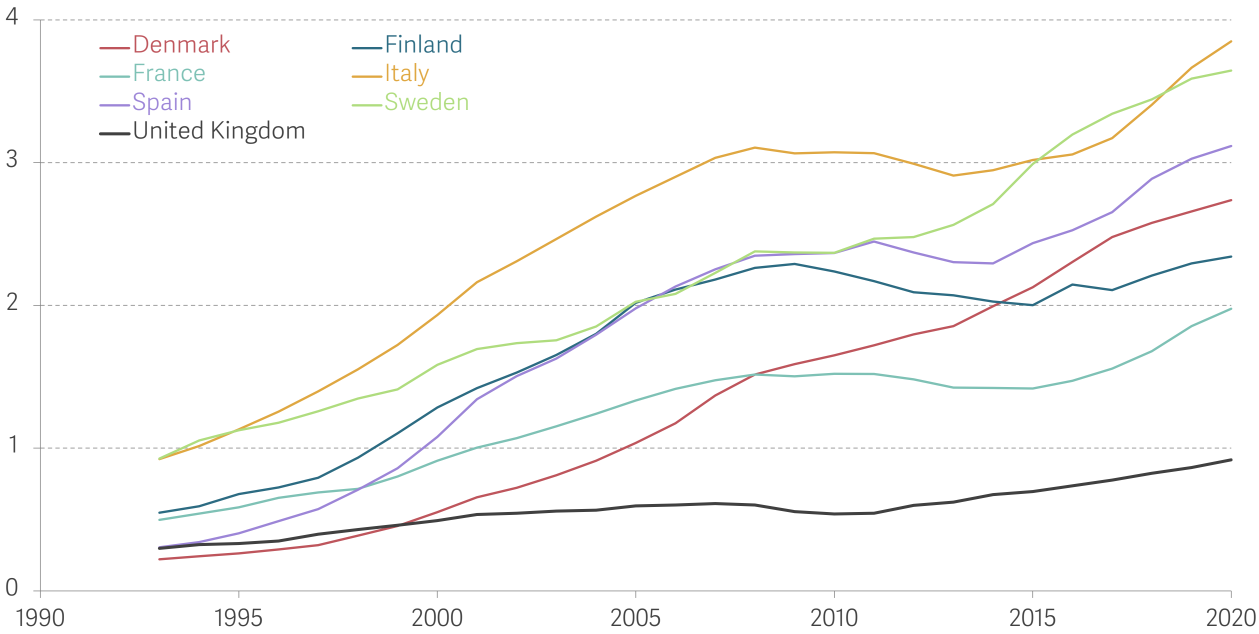
based analysis inspired in the work by Daron Acemoglu and Pascual Restrepo looking at the effects of the adoption of fully automated robots in the US local labour market outcomes.[25]

The United Kingdom has been lagging behind its European counterparts in terms of robot adoption, but has experienced productivity gains in industries adopting more robots

Over the past 30 years, the UK's robot stock has grown, but at a slower rate than its European counterparts, as presented in Figure 7. Using data from the International Federation of Robotics (IFR), we conclude that robot density in UK (number of robots per thousand workers) has grown from 0.30 in 1993 to 0.66 in 2019, while Spain which started with a very similar robot density in 1993 has ended 2019 with a density of 3.07 robots per thousand workers. We note that, despite a slowdown in robot installations in the wake of the Great Financial Crisis, this pattern of relative slower growth in robot adoption in the UK is true when comparing to other similar European countries.[26]

FIGURE 7: **UK stock of robots has been significantly lower and increasing more timidly than its European counterparts.**

Stock of automated robots per thousand workers by country: selected European countries, 1993-2020



NOTES: Stock of automated robot normalized by employment numbers in 1993 by country
SOURCE: CEP analysis of IFR and EUKLEMS

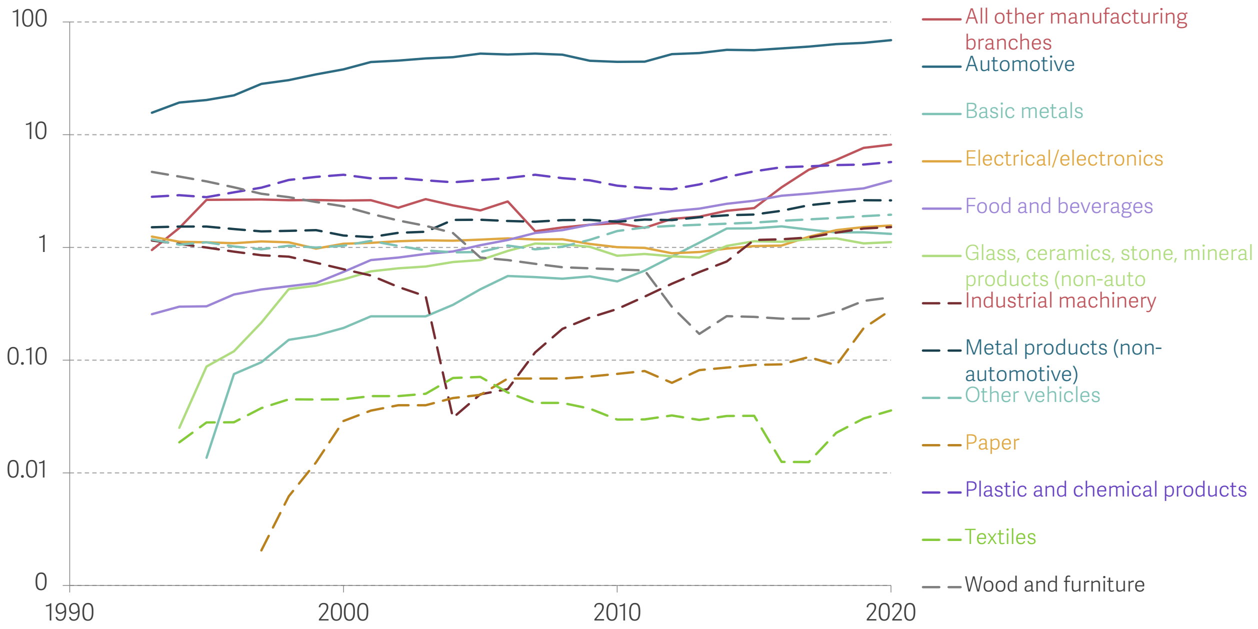
25 D Acemoglu & P Restrepo, 'Robots and jobs: Evidence from US labor markets', June 2020.
26 France, Finland, Denmark, Sweden, and Italy have robot densities of 1.9, 2.13, 2.21, 2.60, and 4.12 in 2019, respectively.

Other major economies like Germany, South Korea and Japan (not shown in the chart) have seen even higher rates of robot adoption than those of the UK and other European countries (see Figure 7).[27]

Not all industries have adopted robot technologies at the same rate in the UK. As shown in Figure 8, the automotive industry has seen the fastest growth in robot density compared to other industries, while textiles and wood and furniture have seen a decline in robot density. The differences in the speed of robot installations across industries mean that workers have been exposed to this technology differentially depending on the industry they work in.

FIGURE 8: **Growth in robot adoption in the UK differs significantly by industry of use**

Stock of automated robots per thousand workers by industry: UK, 1993-2020



NOTES: Stock of automated robot normalized by employment numbers in 1993 by industry
SOURCE: CEP analysis of IFR and EUKLEMS

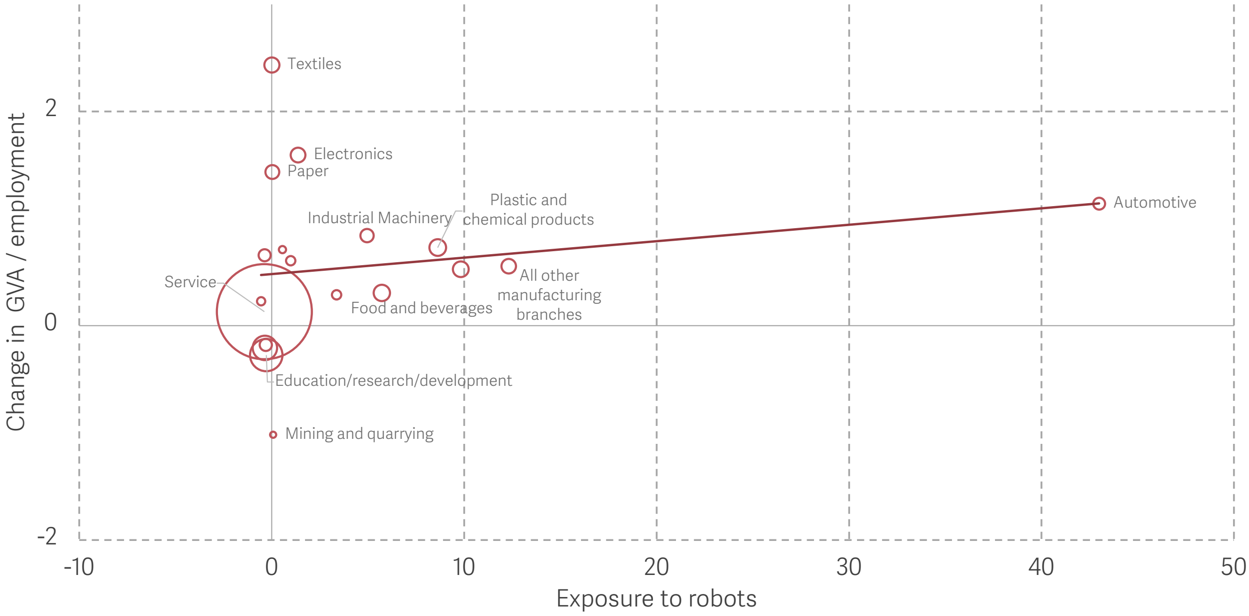
Linking to the debate on the different economic effects of technological change, it is important to note that industries that experienced faster adoption of robots have seen higher productivity gains, as would be predicted. Figure 9 shows the positive effect of robot adoption on productivity growth (GVA per worker) across industries in the UK economy using an Instrumental Variable (IV) modelling and estimation – a positive and statistically significant coefficient of 0.03 is estimated. The use of the IV model addresses potential biases in the estimation of the relationship that can be driven, for example, by selective adoption of robots in response to poor productivity performance of certain UK

27 For a detailed analysis please see: G Graetz & G Michaels, 'Robots at work', December 2018.

industries. This estimate means that an industry with one additional robot per thousand workers experienced 3 per cent faster growth in productivity between 1995 and 2019 in the UK - evidence consistent with a productivity effect of robot adoption across UK industries during this period.

FIGURE 9: **Productivity has gained from robot adoption in UK industries**

Change in GVA per worker and automated robots per thousand workers by industry: UK,1995-2019



NOTES: Figure shows the estimated IV model coefficient between difference in log of GVA per worker and robot exposure (change in robots stock divided by initial employment) at the level of 19 industries between 1995-2019. The instrument of the IV model is robot exposure averaged over 6 European countries (Denmark, France, Finland, Italy, Spain and Sweden). Regression is weighted by industry employment level in 1995.
SOURCE: CEP analysis of IFR and EUKLEMS.

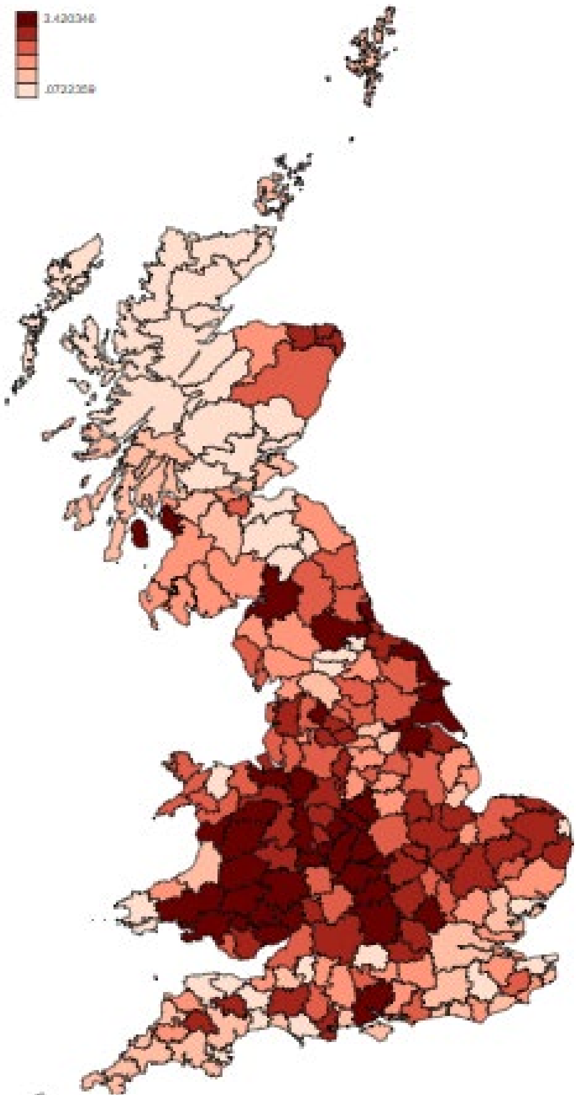
Great Britain's local labour markets have been affected differently by robot exposure but the long-term effects seem to cancel each other

After documenting the UK trends in robot installations of different industries and its relationship with productivity we are interested in addressing the question of how technology, in particular robots, has affected employment opportunities across local labour markets in the UK context. In order to construct a measure of exposure to robots at local labour market level we rely on the premise that the industry-level employment industry composition of a given local labour market in the beginning of the period of analysis is a useful measure to understand how much robot exposure that geography faced.

Industry composition differs across local labour markets and industries adopted robot technology at different speeds implying that some areas of the country have been significantly more exposed to robot installations than others.[28] We map the levels of exposure to robots for the different local labour markets of Great Britain in Figure 10.[29] Looking at the map one can see that high exposure areas are concentrated in Wales and West Midlands, however other areas outside these regions of Great Britain have seen equally high robot adoption.

FIGURE 10: **Local areas in Britain have vastly different exposure of robots in the past 25 years, Rugby being the most exposed and Minehead the least**

Robot exposure by travel to work area: GB, 1995 to 2019



NOTES: Details on robot exposure construction available in the Appendix.
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

28 Please see the Appendix for the formal details of the construction of the local labour market exposure levels.
29 Local labour markets are defined as travel-to-work areas as defined by the 2001 Census. Unfortunately, obtaining consistent data necessary for our analysis for Northern Ireland Is challenging.

We proceed to study how exposure robot adoption has affected employment levels across travel-to-work areas between 1995 and 2019. We first look at the overall effect on local employment-to-population ratios. In contrast to the negative employment effects in the US, we find no such negative link between exposure to robots and aggregate level of employment in Great Britain.[30]

Table 1 presents the results of econometric analysis conducted, where Column (1) shows that both econometric models (OLS and IV)[31] produce positive but statistically insignificant estimates of the effects of higher robot exposure on total employment-to-population ratios[32]. However, what becomes clear from the estimates in Columns (2) and (3) is that the overall effect masks opposing effects in manufacturing and non-manufacturing jobs. Within manufacturing, the installation of robots has significantly reduced manufacturing jobs, while in the non-manufacturing sector labour demand appears to have expanded resulting in offsetting gains in employment.

Once more, the IV model and estimation is used, in order to minimize biases arising from measurement error and endogenous supply and demand responses. Figure 11 shows the overall and separate effects of exposure to robots across local labour markets in Great Britain. These results are suggestive of the presence of both negative displacement effects and positive productivity and augmentation effects in UK local labour markets during this period.

30 A relevant point to be made when discussing possible comparisons with the studies conducted in the US relates to the period of analysis: the US most extended period of analysis is between 1990 and 2014. Please see the Appendix for a discussion on the differences between time periods and how these main results do not change.
31 The model explanation Is provided in detail In the Appendix.
32 A discussion of the appropriateness of the two modelling approaches Is discuss In the Appendix.

TABLE 1: **Effects of Robots on Employment Across Local Labour Markets**

Change in Employment-to-Population Ratio 1995-2019 (x100)

	(1) Total	(2) Manufacturing	(3) Non-Manufacturing
A. OLS			
Exposure to Robots	0.867	0.020	0.847
1995-2019	(0.704)	(0.367)	(0.585)
B. IV			
Exposure to Robots	1.336	-0.917**	2.252**
1995-2019	(1.287)	(0.465)	(1.091)
C. First-Stage			
Euro6 Exposure to Robots	0.338***	0.338***	0.338***
1995-2019	(0.063)	(0.063)	(0.063)
F-Stat	29.006	29.006	29.006
Sample Size	232	232	232
Regions	✓	✓	✓
Demographics	✓	✓	✓
Industry Shares and Routine Jobs	✓	✓	✓

NOTES: Sample of 232 TTWA in Great Britain. Dependent variable defined as ratio between employment and population. Columns (2) and (3) restrict employment denominator to manufacturing and non-manufacturing sectors respectively. Panel A are Ordinary Least Squares (OLS) regression estimates. Panel B are Instrumental Variable (IV) estimates where UK exposure is instrumented with the shift share of exposure to robots of 6 European countries (Denmark, France, Finland, Italy, Spain and Sweden) weighted by TTWA industry employment structure in 1984. Panel C reports the first-stage estimates of the IV model. All specification control for NUTS II fixed effects, demographic controls measured by the 1991 Census (shares of White, Asian, Black populations, share of non-native population, share of high skilled (qualified) workers in employment, share of female population and share of population over 65), industry shares in 1991 (share of light manufacturing employment) and share of routine jobs in 1991. All regressions weighted by TTWA population in 1991. Standard errors are reported in parentheses and clustered at NUST II level (Nc = 34). Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Further details on variable construction available in the Appendix.
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

FIGURE 11: **The overall employment effect of robot adoption across local labour markets in the GB was neutral and insignificant, but it hides differences between sectors**

Long difference relation between robot exposure and employment-population ratios: 1995-2019

NOTES: Each point represents a TTWA, size of the marker proportional to the population in 1991. Plots based on the regressions specification presented Column(2) of the Appendix Table C1.
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

The adoption of robots in Great Britain has presented challenges as well as opportunities

As mentioned in the beginning of this report it is often the case that the more immediate job loss impacts of technology are the ones making it to headlines of the media outlets, while the longer-run job creation effects in the economy as whole are overlooked. Adoption of robots in Great Britain has created challenges as well as opportunities and, on average, local labour markets appear to have been able to adjust in the long run.

While there might be long-run adjustment, there are winners and losers in this process. Workers who have been displaced and had difficulties in adjusting faced hardship, and some areas of the country have seen their industrial composition landscape change significantly. Considering the estimated magnitude of the robot automation effect on manufacturing jobs and assuming that this effect is broadly uncorrelated with other economic shocks affecting the economy during the period of analysis, it is estimated that 1 in each 4.7 manufacturing jobs per 100 people lost during the period of 1995 to 2019 can be explained by the expanding adoption of automated robots. The magnitude of this effect can be compared to the estimated 1.5 in each 4 manufacturing jobs per 100 people lost in the period from 2000 to 2015 attributed to the increase in import competition from China affecting the UK.[33] The previous quantification shows that automation, as measured in this analysis, had a similar (if not lower) relative contribution for the decline in manufacturing employment than that of the China import shock in the past decades. The adoption of robots has accounted for 21 per cent of the manufacturing decline, whereas the import competition driven by China trade expansion has contributed for 38 per cent of the employment contraction observed in manufacturing industries. China's emergence as a great international trade player is an example of a myriad of other shocks to which the UK economy, and in particular the manufacturing sector, has been exposed to during this period. However, despite the negative effects found in the manufacturing employment, it remains true that, albeit with a different underlying sectoral composition, the levels of employment in the UK economy are now higher than in the beginning of the period.

Conclusion

This briefing note provided a short analysis on the how labour markets in the UK have responded to the different waves of technology over the past four decades. Both occupation and local labour market results show the varied nature of technological change impacts on jobs and pay prospects. We find support in favour of both negative and positive effects stemming from the adoption of new technologies, albeit unequally distributed across workers contingent on their occupation and industry. Analogously to the debate over globalization, the focus for policymakers should not be to stop or prevent technological advancements that strongly contribute to create desirable increases in added value and productivity.[34] Instead, the policy conversation should be directed at how to best prepare and retrain workers at risk of being adversely affected by automation technologies. Unfortunately, the UK's track record is not encouraging. As shown in the Economy 2030 Inquiry, workers performing routine tasks (hence more exposed to automation) have experienced larger falls in terms of on-job training and were more likely to hold low qualifications and relatively non-transferable skills.[35] In addition, job mobility in the UK labour market has steadily declined in recent decades with most of the changing across industries being driven by entry and exit rather than direct job-to-job transitions.[36]

33 The calculations are based on the estimates from F Foliano & R Riley, 'International Trade and UK de-industrialisation', October 2017, adjusted to manufacturing jobs per hundred people.
34 J Oliveira-Cunha, J Kozler, P Shah, G Thwaites & A Valero, 'Business time. How ready are UK firms for the decisive decade?', The Resolution Foundation, November 2021.
35 M Brewer, R Costa, A Eyles, K Henehan & S McNally, 'Train In Vain? Skills, tasks, and training in the UK labour market', The Resolution Foundation, 2022
36 N Cominetti, R Costa, A Eyles,T Moev, & G Ventura, 'Changing jobs? Change in the UK labour market and the role of worker mobility', The Resolution Foundation, January 2022.

A careful investigation of the effects of automation at lower level of aggregation (workers, households and firms) is required if one aims at formulating efficient policies which minimise negative displacement effects of technology and ensure that gains in productivity and from reinstatement are more equally spread. These points will be further elaborated in the The Pissarides Review into the Future of Work and Wellbeing, funded by the Nuffield Foundation.

Data Appendix

A1. Crosswalk between US SOC and UK SOC

The matching and mapping methodology from Dickerson and Morris (2019) is adopted to crosswalk the US Occupational Information Network (O*NET) database to UK. First, O*NET data from different versions is converted to a common classification, weighting by the US occupational employment. Second, a matching matrix to convert O*NET SOC to the UK SOC is established with the correspondence table from LMI for All. We then use O*NET SOC employment to create UK occupational information as weighted averages of O*NET occupational information.

A2. Crosswalk between LAD and TTWA

Local authority districts (LAD) are defined according to their classification prior to 2015. Travel-to-work areas (TTWAs) classification and boundaries correspond to the 2001 version produced based on the Census commuting data. To crosswalk LADs to TTWAs we use the 2009 ONS Postcode Directory (ONSPD) and proportionally allocate LADs to TTWA according to the share of postcodes communal to both geographical units. We use information on NUTS I and II from ONSPD, because some LADs and TTWAs cross borders of the NUTS I and II boundaries we attribute NUTS I and II identifiers according to the highest share of postcodes covered.

A3. Crosswalk between UK SOC versions

We measure occupations according to the UK SOC 2010 classification. In order to do so across the time period studied we to use several proportional mappings between different UK SOC vintage classifications. These mappings are applied sequentially to the UK SOC vintages as to harmonize the data in accordance with UK SOC 2010 classification for which we have the measures of technological exposure.

A4. Robot Data

Robot stock is collected from International Federation of Robotics (IFR) and employment data across industries is from EU KLEMS. To keep comparable industrial classification, we adopt the International Standard Industrial Classification of All Economic Activities (ISIC Rev.4). Nineteen industries are kept in the analysis. Six broad non-manufacturing industries: agriculture, forestry, and fishing; mining; utilities; construction; education, research, and development; and services. Thirteen manufacturing industries: food and beverages, textiles (including apparel), wood and furniture, paper and printing, plastics and chemicals, minerals, basic metals, metal products, industrial machinery, electronics, automotive, other vehicles, and other manufacturing branches. In addition to the raw robot stock data, we also construct a stock of robots using both the perpetual inventory method with 10% depreciation and the fully depreciation method with 12 years of depreciation. It turns out that the results are robust with those measures.

A5. Gross Value Added Data

Gross value added (GVA) across industries and countries is compiled from OECD, measured in constant prices at the base year.

A6. Covariates Data

Data on demographic covariates is obtained via NOMIS from the 1991 Census. Number of population foreign born, Asian, Black, White and aged above 65 are retrieved at LAD level. Number of employed individuals in routine jobs as defined in Autor and Dorn (2013) is equally retrieved at LAD level.

A7. Employment and Population Data

Employment and population data are obtained from NOMIS at LAD level. Employee data is further aggregated and harmonised to industry classification SIC 2007 at two-digit level. Furthermore, employment numbers are adjust following the work by Robert Jump as to match the official regional job counts from the Workforce Jobs data[37].

37 R Jump, 'A Dataset of Workforce Job Counts for British Local Authority Districts, 1981-2018', December 2020.

Technical Appendix

B1. Occupational Exposure (Robots, Software and AI)

The occupational analysis is conducted using employment weighted rank percentiles of exposure scores. Firstly, exposure scores are standardized to have mean 0 and standard deviation 1 using employment weights in 1981. Secondly, employment weighted ranks are calculated across occupations using once more the employment weights of the initial period, 1981.

The following model equation is estimated using ordinary least squares (OLS):

$$\Delta y_o \;=\; \gamma Z_o' + \delta \mathrm{Exp_o} + u_o$$

The outcome variable Δy_o is defined as either the DHS changes in employment shares or changes in log weekly full-time real wages between 1981 and 2019. Controls for other demand factors (offshoring, education levels) and demographics (share of female, age band shares) are included in the vector Z_o'. The unit of analysis *o* denotes occupation (UK SOC 2010 4 digit classification) and when possible occupation-industry cells (UK SOC 2010 4 digit classification by UK SIC 1992 industry section).

B2. Regional Robot Exposure

Regional robot exposure is constructed following Acemoglu and Restrepo (2020). First, we construct the two measures of penetration of robots in industry *i* (unadjusted and adjusted) as follows

$$PR_{i,(t_0,t_1)}^{UK} = \frac{M_{i,t_1}^{UK} - M_{i,t_0}^{UK}}{L_{i,1993}^{UK}}$$

$$APR_{i,(t_0,t_1)}^{UK} = \frac{M_{i,t_1}^{UK} - M_{i,t_0}^{UK}}{L_{i,1993}^{UK}} - g_{i,(t_0,t_1)}^{UK} \frac{M_{i,t_0}^{UK}}{L_{i,1993}^{UK}}$$

Where $M_{i,t}$ is the robot stock of industry *i* at time t, $g_{i,(t_0,t_1)}$ is the growth rate of output of industry *i*, $L_{i,1993}$ represents the baseline employment level in industry *i*, we take $t_0 = 1993$ and $t_1 = 2019$ to study long-term effects. Regional robot exposure thus is a Bartik-style measure combining industry-level variation in the usage of robots and baseline employment shares, which we first construct at the local authority level and then convert it to travel-to-work areas,

$$\text{UK exposure to robots}_c = \textstyle\sum_i l_{ci} \times APR_i^{UK},$$

Where l_{ci} is the baseline employment share of industry *i* in local authority *c*, which we use 1993 levels.

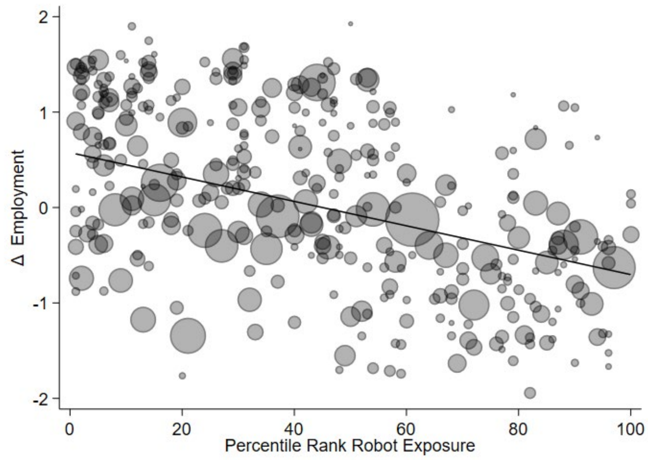
We estimate our models using the ordinary least squares (OLS) and instrumental variable (IV) method. With the measure of regional robot exposure, we can estimate

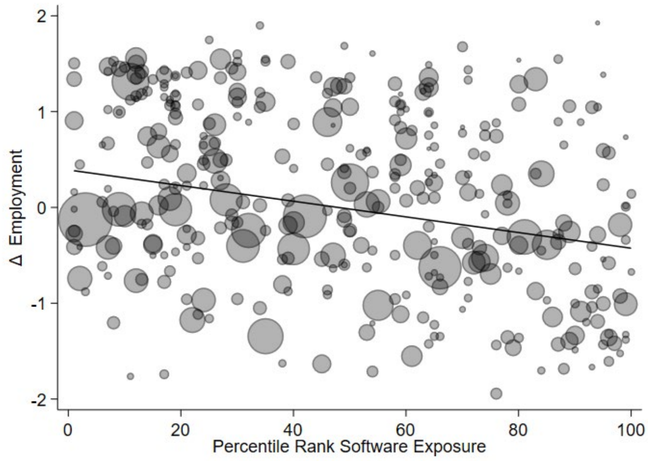
$$\Delta y_c = \alpha X_c' + \beta \Delta \text{robots}_c + \epsilon_c$$

We regress changes of employment-to-population ratio on the change in the UK regional exposure to robots, Δrobots_c . In the vector X_c', we control for regional effects, baseline industrial share and demographic characteristics such as gender, race and age. The UK robot exposure can be correlated with the error term for two reasons, which biases our estimates as a consequence of endogeneity. The first reason is that industrial policy may result in some industries adopting more robots while at the same time increasing the demand for labour. Second, any regional shocks affecting labour demand and decisions made by local businesses, such as the adoption of robots, may also influence our estimates. Therefore, IV method is used to address the endogeneity issue of UK exposure to robots. A shift-share IV is constructed using robot adoptions across industries in other high-income European countries. Six European countries we choose are Denmark, Finland, France, Italy, Spain and Sweden[38]. We first calculate the average penetration of robots in industry *i* across European countries and construct the IV as the weighted average of the average APR of six European countries, using the UK regional employment shares of 1984 as the share.

38 In this study, we selected European countries with comparable levels of robot adoption as the UK. In countries like Germany, robot adoption is much advanced, so they are not used.

A. Regression Analysis – Exposure to Robot, Software and AI





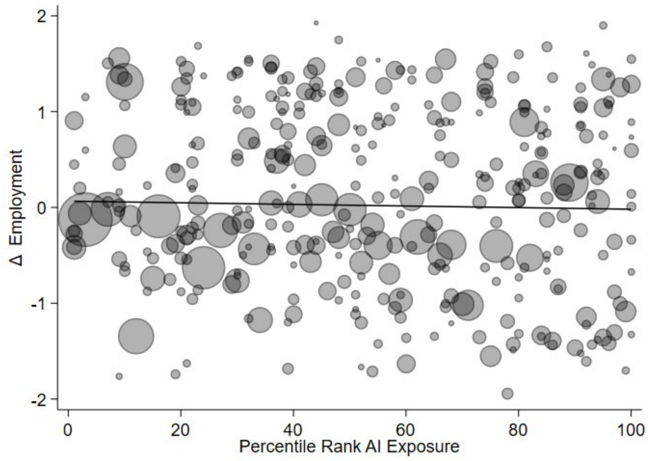


Table C1 – Changes in Wages vs Technological Exposure, 1981-2019 – Occupation Level

	Changes in Employment Shares (×100)			
	(1)	(2)	(3)	(4)
A. Rank Robot	-1.278***	-0.987***	-0.997***	-0.756***
	(0.137)	(0.141)	(0.155)	(0.173)
R^2	0.194	0.289	0.289	0.315
B. Rank Software	-0.817***	-0.729***	-0.700***	-0.504***
	(0.145)	(0.144)	(0.144)	(0.148)
R^2	0.080	0.245	0.256	0.301
C. Rank AI	-0.084	-0.290*	-0.279*	-0.299*
	(0.147)	(0.156)	(0.154)	(0.154)
R^2	0.001	0.199	0.214	0.286
N	366	366	366	366
	Covariates			
Demographic		Y	Y	Y
Offshoring			Y	Y
Education				Y

NOTES:. Each observation is an occupation cell. Changes in employment is measured as DHS change of each occupation share of employment between 1981 and 2019. Exposure ranks are calculated as the employment weighted percentiles of the corresponding standardized exposure score according to the 1981 employment structure. Demographic controls include unit level shares of females and age bands in 1981. Occupation level offshoring standardized score is defined as in Autor and Acemoglu (2011). Education controls are shares of dropout, high school graduates, some college and college or higher for each occupation in 1981. All regressions are weighted by mean employment between 1981 and 2019. Standard errors are report in parentheses. Statistical significance is denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE: CEP analysis of LFS and Michael Webb (2020)

Table C2 – Changes in Wages vs Technological Exposure, 1981-2019 – Occupation Level

	Changes in Log FT Weekly Real Wages (×100)			
	(1)	(2)	(3)	(4)
A. Robot Exposure	-0.175***	-0.191***	-0.222***	-0.201***
	(0.034)	(0.036)	(0.039)	(0.044)
R^2	0.067	0.164	0.172	0.191
B. Software Exposure	-0.031	-0.085**	-0.084**	-0.063*
	(0.036)	(0.037)	(0.037)	(0.038)
R^2	0.002	0.110	0.110	0.149
C. AI Exposure	0.173***	0.109***	0.110***	0.091**
	(0.033)	(0.038)	(0.038)	(0.039)
R^2	0.070	0.117	0.118	0.156
N	366	366	366	366
	Covariates			
Demographic		Y	Y	Y
Offshoring			Y	Y
Education				Y

NOTES:. Each observation is an occupation cell. Changes in wages is measured as change in log full-time weekly real wages for each occupation between 1981 and 2019. Exposure ranks are calculated as the employment weighted percentiles of the corresponding standardized exposure score according to the 1981 employment structure. Demographic controls include unit level shares of females and age bands in 1981. Occupation level offshoring standardized score is defined as in Autor and Acemoglu (2011). Education controls are shares of dropout, high school graduates, some college and college or higher for each occupation in 1981. All regressions are weighted by mean employment between 1981 and 2019. Standard errors are report in parentheses. Statistical significance is denoted by: * p < 0.10, ** p < 0.05, *** p < 0.01.
SOURCE: CEP analysis of ASHE and Michael Webb (2020)

Table C3 – Changes in Employment vs Technological Exposure, 1981-2019 – Occupation-Industry Level

	Changes in Employment Shares (×100)			
	(1)	(2)	(3)	(4)
A. Robot Exposure	-0.874***	-0.821***	-0.724***	-0.566***
	(0.166)	(0.159)	(0.160)	(0.170)
R^2	0.344	0.381	0.384	0.394
B. Software Exposure	-0.367*	-0.470***	-0.421***	-0.286*
	(0.180)	(0.158)	(0.139)	(0.149)
R^2	0.304	0.353	0.368	0.385
C. AI Exposure	0.254	-0.041	-0.045	-0.097
	(0.160)	(0.131)	(0.115)	(0.106)
R^2	0.300	0.340	0.358	0.381
N	4168	4168	4168	4168
	Covariates			
Industry Dummies	Y	Y	Y	Y
Demographic		Y	Y	Y
Offshoring			Y	Y
Education				Y

NOTES:. Each observation is an occupation-industry cell. Changes in employment is measured as DHS change of each occupation-industry share of employment between 1981 and 2019. Exposure ranks are calculated as the employment weighted percentiles of the corresponding standardized exposure score according to the 1981 employment structure. Industry dummies denote 19 industry fixed effects. Demographic controls include unit level shares of females and age bands in 1981. Occupation level offshoring standardized score is defined as in Autor and Acemoglu (2011). Education controls are shares of dropout, high school graduates, some college and college or higher for each occupation-industry in 1981. All regressions are weighted by mean employment between 1981 and 2019. Standard errors are clustered at industry level (Nc = 19) and report in parentheses. Statistical significance is denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.
SOURCE: CEP analysis of LFS and Michael Webb (2020)

Robustness Checks – Local Labour Markets Analysis

The following table show some robustness checks to the analysis presented in the report. Table D1 shows the stability of the main estimates of Table 1 across different set of covariates used, the preferred specification that is used in the main table corresponds to Column (3) of Table D1. In Table D2 we narrow the period of analysis between 1995 and 2007 as to allow a better comparison with the US study by Acemoglu and Restrepo (2020). Although the overall effect in column (1) is estimated to be negative when this time period is considered, it remains statistically insignificant[39]. More importantly and in contrast to the US effects, in Columns (2) and (3) we do not find any evidence of employment losses beyond the manufacturing sector. Finally, Table D3 shows the estimated effects using different measures of robot penetration. Firstly, Column (1) shows our baseline measure which consists of the unadjusted robot penetration based of robot stocks consistent with 12-year full depreciation. Secondly, Column (2) repeats the estimation using the raw robot stocks of IFR without any depreciation assumption. Thirdly, in Column (3) we construct the measure according to the perpetual inventory method used by Graetz and Michaels (2018). And finally, in Column (4) we use the adjusted penetration measure proposed by Acemoglu and Restrepo (2020) that account for each industry's output growth. Reassuringly the estimates across measures show the same sign and similar levels of statistical (in)significance. We further calculate the implied effect at the average level of exposure as measures vary significantly in magnitude hence are not directly comparable by looking at the estimated coefficients. Once scaled to their respective mean, the effects across measures are quite similar in their adjusted magnitude.

39 During the drafting of this report, we were pointed to the work by C Chen & C Frey, 'Automation or Globalization? The Impacts of Robots and Chinese Imports on Jobs in the United Kingdom' , August 2021, who conduct a similar UK analysis at LAD level for the period 1991-2007. Despite getting a similar magnitude of the estimated the overall effect, we fail to find statistical significance. The analyses have differences in the unit and period of analysis that may help explain the discrepancy.

Table D1 – Effects of Robots on Employment, Different Specifications

	Change in Employment-to-Population Ratio 1995-2019 (×100)		
	(1)	(2)	(3)
A. **OLS**			
Exposure to Robots	0.455	0.521	0.867
	(0.701)	(0.634)	(0.704)
B. **IV**			
Exposure to Robots	1.356	1.015	1.336
	(1.218)	(1.188)	(1.287)
C. **First-Stage**			
Exposure to Robots	0.359***	0.358***	0.338***
	(0.068)	(0.067)	(0.063)
F-Stat	28.090	28.297	29.006
Sample Size	232	232	232
	Covariates		
Regions	Y✓	Y✓	Y✓
Demographics		Y✓	Y✓
Industry Shares and Routine Jobs			Y✓

NOTES:. Sample of 232 TTWA in Great Britain. Dependent variable defined as ratio between employment and population. Panel A are Ordinary Least Squares (OLS) regression estimates. Panel B are Instrumental Variable (IV) estimates where UK exposure is instrumented with the shift share of exposure to robots of 6 European countries (Denmark, France, Finland, Italy, Spain and Sweden) weighted by TTWA industry employment structure in 1984. Panel C reports the first-stage estimates of the IV model. Column (1) specification controls for NUTS II fixed effects. Column (2) adds demographic controls measured by the 1991 Census (shares of White, Asian, Black populations, share of non-native population, share of high skilled (qualified) workers in employment, share of female population and share of population over 65). Column (3) adds industry shares in 1991 (share of light manufacturing employment) and share of routine jobs in 1991. All regressions weighted by TTWA population in 1991. Standard errors are reported in parentheses and clustered at NUST II level (Nc = 34). Statistical significance denoted by: * p < 0.10, ** p < 0.05, *** p < 0.01
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

Table D2 – Effects of Robots on Employment – 1995-2007

	Change in Employment-to-Population Ratio 1995-2007 (×100)		
	Total	Manufacturing	Non-Manufacturing
A. **OLS**			
Exposure to Robots	0.136	-0.236	0.373
1995-2007	(0.809)	(0.326)	(0.604)
B. **IV**			
Exposure to Robots	-1.164	-1.274^{**}	0.110
1995-2007	(1.521)	(0.518)	(1.263)
C. **First-Stage**			
Euro6 Exposure to Robots	0.323^{***}	0.323^{***}	0.323^{***}
1995-2007	(0.058)	(0.058)	(0.058)
F-Stat	30.844	30.844	30.844
Sample Size	232	232	232
	Covariates		
Regions	Y✓	Y✓	Y✓
Demographics	Y✓	Y✓	Y✓
Industry Shares and Routine Jobs	Y✓	Y✓	Y✓

NOTES:. Sample of 232 TTWA in Great Britain. Dependent variable defined as ratio between employment and population. Columns (2) and (3) restrict employment denominator to manufacturing and non-manufacturing sectors respectively. Panel A are Ordinary Least Squares (OLS) regression estimates. Panel B are Instrumental Variable (IV) estimates where UK exposure is instrumented with the shift share of exposure to robots of 6 European countries (Denmark, France, Finland, Italy, Spain and Sweden) weighted by TTWA industry employment structure in 1984. Panel C reports the first-stage estimates of the IV model. All specification control for NUTS II fixed effects, demographic controls measured by the 1991 Census (shares of White, Asian, Black populations, share of non-native population, share of high skilled (qualified) workers in employment, share of female population and share of population over 65), industry shares in 1991 (share of light manufacturing employment) and share of routine jobs in 1991. All regressions weighted by TTWA population in 1991. Standard errors are reported in parentheses and clustered at NUST II level (Nc = 34). Statistical significance denoted by: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

Table D3 – Alternative Exposure Measures

	Change in Employment-to-Population Ratio 1995-2019 (×100)			
	(1)	(2)	(3)	(3)
	12-year Depreciation Exposure	Raw Exposure	Perpetual Inventory Exposure	Adjusted Exposure
IV				
Exposure to Robots $(\hat{\beta})$	1.336	1.384	2.349	2.724
	(1.287)	(1.581)	(2.486)	(2.361)
First Stage F-Stat	29.006	29.444	29.254	29.393
Effect at the Mean $(\hat{\beta} \times \overline{Exposure})$	0.988	0.786	0.813	1.207
Sample Size	232	232	232	232

NOTES:. Sample of 232 TTWA in Great Britain. Dependent variable defined as ratio between employment and population. Regression coefficients are Instrumental Variable (IV) estimates where UK exposure is instrumented with the shift share of exposure to robots of 6 European countries (Denmark, France, Finland, Italy, Spain and Sweden) weighted by TTWA industry employment structure in 1984. Columns (1) to (4) estimate the model with alternative robot exposure measures describe in the Appendix. All specification control for NUTS II fixed effects, demographic controls measured by the 1991 Census (shares of White, Asian, Black populations, share of non-native population, share of high skilled (qualified) workers in employment, share of female population and share of population over 65), industry shares in 1991 (share of light manufacturing employment) and share of routine jobs in 1991. All regressions weighted by TTWA population in 1991. Standard errors are reported in parentheses and clustered at NUST II level (Nc = 34). Statistical significance denoted by: * p < 0.10, ** p < 0.05, *** p < 0.01
SOURCE: CEP analysis of IFR, EUKLEMS and NOMIS

THE
ECONOMY 2030
INQUIRY
SHAPING A DECADE OF CHANGE

The UK is on the brink of a decade of huge economic change – from the Covid-19 recovery, to exiting the EU and transitioning towards a Net Zero future. The Economy 2030 Inquiry will examine this decisive decade for Britain, and set out a plan for how we can successfully navigate it.

The Inquiry is a collaboration between the Resolution Foundation and the Centre for Economic Performance at the London School of Economics. It is funded by the Nuffield Foundation.

For more information on The Economy 2030 Inquiry, visit economy2030.resolutionfoundation.org.

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