Automation or Globalization? The Impacts of Robots and Chinese Imports on Jobs in the United Kingdom*

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Abstract

In this paper, we examine how robot adoption and Chinese import competition shaped employment patterns in 352 cities across the United Kingdom. We find that cities whose initial industry composition exposed them to industrial robots and China's integration into the world economy experienced significant employment declines. When pitched against other capital and technologies, the impact of robots remains distinct. Our findings suggest that one more robot per thousand workers reduced the employment-to-population ratio by 0.5 percentage points, while an increase of $1,000 imports from China per worker reduced the employment-to-population ratio by 0.11 percentage points. We also show that while these are sizable effects, penetration of both robots and Chinese imports are too small to account for Brexit.

Keywords: Robots, trade, cities, employment, Chinese imports

JEL codes: R11, O31, O33

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1 Introduction

Technology and trade are widely regarded the key forces shaping labor markets in the industrial world over the past four decades (Autor et al. 2016, Baldwin 2019, Brynjolfsson & McAfee 2014, Frey 2019, Frey & Osborne 2017). Computer-controlled machines allow companies to automate routine tasks previously performed by middle-income workers (Autor et al. 2013). But computers also enable corporations to coordinate production at distance, allowing them to tap into pools of cheap labor in developing countries (Baldwin 2016). While there have been efforts to disentangle the labor market impacts of technology and trade in the United States (Autor et al. 2015), their relative importance in putting pressure on jobs and wages in Europe remains poorly understood.[1]

In this paper, we disentangle the effects of robots and Chinese import competition on local labor markets in the England, Scotland and Wales. The United Kingdom is an interesting case, because it allows us to explore a key feature of the task-based model: that automation is subject to diminishing productivity returns (Acemoglu & Restrepo 2018).[2] As shown in Panel A of Figure 1, the UK has a substantially lower penetration of robots relative to other advanced economies across industries.[3] Therefore, a larger productivity effect should help offset the direct displacement effect, implying that adverse employment impacts of trade and technology should be relatively muted, when pitched against other high-income countries (for a formal model, see Appendix A). Panel B of Figure 1 also shows that in several industries, the United Kingdom has a lower penetration of Chinese imports

[1]While Aghion et al. (2020) and Bonfiglioli et al. (2020) study the impact of robots in France, these papers do not seek to disentangle their impact from Chinese import competition.

[2]For example, Calì & Presidente (2022) document diminishing returns to robot adoption in Indonesia and across countries. The UK case is also particularly interesting because it allows us to shed some light on the widely discussed political economy implications of technological change and globalization, such as the widespread perception of both being key drivers of the recent rise of populism in the context of Brexit.

[3]IFR (2021), for instance, notes: "As the only G7 country – the UK has a robot density below the world average of 126 units with 101 units, ranking 24th. Five years ago, the UK´s robot density was 71 units." https://ifr.org/ifr-press-releases/news/robot-density-nearly-doubled-globally

relative to its counterparts in the OECD. This runs counter to the popular perception that economic hardship caused by technology and trade is partly responsible for recent political events, like Brexit.[4]

Specifically, we examine the impact of industrial robots and exposure to Chinese imports across 352 local authority district areas—which we refer to as "cities" throughout the paper. For our analysis, we construct a measure of exposure to automation using data from the International Federation of Robotics (IFR) on the uptake of robots across 18 industries and their respective baseline employment shares at the dawn of the robot revolution. Thus, the variation in our measure stems from the fact that industrial employment is unevenly distributed across cities, making some places more exposed to automation than others. In similar fashion, we use industry trade data from the UN Comtrade database to capture cities exposure to Chinese imports, where again the variation is in their distribution of industrial employment.

A key concern with our empirical approach is that Chinese imports as well as the adoption of robotics technology in a given UK industry might be related to other confounding variables affecting that industry or cities that have specialized in the production of related goods. To alleviate such concerns, we use the industry-level penetration of robots and Chinese imports in other European or high-income countries as instruments for the exposure of UK industries. Doing so, we follow the approach of Acemoglu & Restrepo (2020) to estimate the employment effects of robots in the UK, as well as Autor et al. (2013, 2015) to estimate the impact of Chinese imports on local labor markets. This strategy allows us to sharpen our focus on the heterogeneity that stems solely from industries where economic outcomes have been shaped by Chinese imports and robot adoption in the industrial world. It also makes our findings comparable to those of previous similar studies.

[4]For example, Becker et al. (2017) find that areas heavily dependent on manufacturing employment were more likely to vote Leave in the EU referendum.

In our regression analysis, we find that both robots and Chinese imports are responsible for non-negligible job losses across UK cities. Our baseline estimate suggests that one additional robot per thousand workers lowers employment by .5 percentage points, which is similar to previously reported estimates for the US, despite the higher robot penetration in the US economy (Acemoglu & Restrepo 2020). Turning to our baseline estimate for the impact of Chinese import competition, we find that a an increase of $1,000 imports from China per worker reduced the employment-to-population ratio by .11 percentage points on average. We note that this effect is smaller in magnitude to previous estimates for the US (Autor et al. 2015). To make the estimated impacts of robots and Chinese imports more comparable, we calculate standardised coefficients, suggesting that one standard deviation increase in exposure would lower employment by a similar order of magnitude—between .13 and .16 percentage points. However, despite these sizable effects, the low penetration of robots and Chinese imports in the UK mean that neither are likely to have shaped the Brexit vote to any meaningful extent. Indeed, we do not find that either globalization or automation is associated with greater support for Vote Leave.[5]

Finally, while we do find some evidence of diminishing returns to automation *within* the United Kingdom, our results imply that the marginal impact of automation has been similar in the UK and the US. One possible explanation for the finding is that while the displacement effect is concentrated locally, the countervailing productivity effect is likely to be more dispersed. Thus, the productivity gains from automation accrued to firms scattered across UK cities might contribute to increase labor demand elsewhere. We note that this is especially likely in a country such as the UK, where foreign multinationals account for a relatively large share of GDP.[6]

[5]While we document a negative impact of robots on the Vote Leave share, the estimated coefficient is not statistically significant.

[6]See Online Appendix Figure III.

Our paper adds to two literatures. First, studies have documented differential impacts of robots on jobs across countries. For example, while there is evidence that robots have reduced employment in the United States (Acemoglu & Restrepo 2020), and in France (Acemoglu et al. 2020), employment losses in the German and Italian manufacturing sectors were offset by job creation in other sectors (Dauth et al. 2021, Dottori 2020). Firm-level evidence from the Netherlands even suggests that robot adoption is associated with faster employment growth (Bessen et al. 2020). More broadly, in a pioneering study of seventeen countries, Graetz & Michaels (2018) find that robots had no significant effect on total hours worked on average. One explanation for the differential impact of robots across countries is that technological change inevitably interacts with different labor market institutions. For example, the relative strength of German trade unions is likely to go some way toward explaining the differences between the US and Germany, as Dauth et al. (2021) argue. Our findings, which are similar to previous results for the US, speak to the notion that there are different varieties of capitalism (Thelen 2014, Hall & Soskice 2001), and that the US and the UK have similar institutions (Acemoglu & Robinson 2013), such as low levels of unionization and collective bargaining coverage (Thelen 2001), yielding similar labor market outcomes.[7]

Second, a series of papers examine how workers in the industrial world have adjusted to the China's integration into the global economy (Autor et al. 2013, Dauth et al. 2021, Autor et al. 2016), while a branch of this literature has focused on disentangling the impacts of trade (e.g. the rise of China) and technology (e.g. the computer revolution), which are roughly contemporaneous events. In particular, Autor et al. (2015) show that local labor markets in the US, which were intensive in routine tasks at the beginning of the investigated period, and thus susceptible to computerization, experienced occupational po-

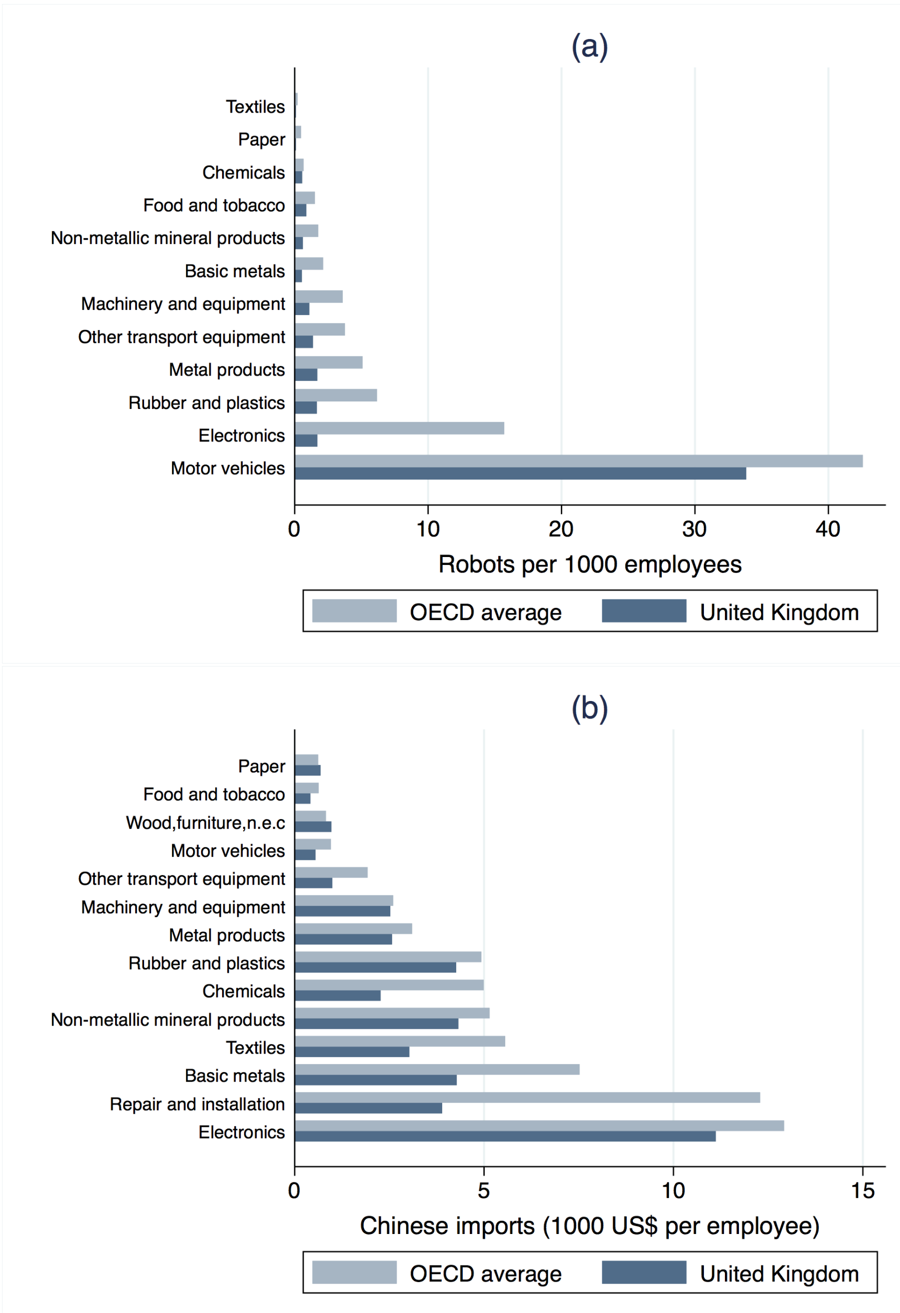
[7] In addition, Belloc et al. (2020) and Presidente (2021) study the role of labor market institutions in explaining differences in investment in automation technologies.

larization, but did not witness net employment declines. In contrast, local labor markets that were exposed to Chinese imports saw significant falls in employment, particularly in manufacturing and among non-college workers. We find that UK cities experienced similar employment declines in response to the rise of China. However, using robots instead of the routine employment share as a more direct measure of exposure to automation technologies, we find that UK cities that were exposed to the robot revolution also experienced large job losses.[8]

The remainder of this paper is structured as follows. In section 2, we describe our data sources. Section 3 outlines our empirical strategy, while section 4 presents our results and several robustness checks. Finally, in section 5, we provide some conclusions.

[8] Foliano & Riley (2017) also examine the impact of Chinese imports on manufacturing employment in the UK. In contrast, we examine the impact of Chinese imports on total employment across UK cities.

Figure 1: UK penetration of robots and Chinese imports relative to the OECD average.



Notes: This figure compares sample averages for the OECD region and in the United Kingdom of (a) the number of industrial robots per 1000 employees; and (b) thousands of US$ of Chinese intermediate inputs.
Source: Authors' calculations based on IFR, TiVA, STAN.

2 Data and Measurement

In the below, we describe the construction of our key variables and the data sources underlying them.

2.1 Robots and adjusted penetration of robots

To measure robot exposure across local labor markets, we use industrial robots data from the International Federation of Robotics (IFR), which provides annual counts of the operational stock of robots at the country-industry level from 1993 onward. Industrial robots is an automation technology, defined by the IFR (2014) as automatically controlled, reprogrammable, and multipurpose machines that are autonomous (i.e., no human operators are required) and can be adapted to perform various tasks flexibly. In other words, our data consists of multipurpose machines capable of handling a variety of tasks, such as assembly, packaging, or welding. The counts of these machines are based on consolidated data provided by nearly all industrial robot suppliers worldwide to the IFR.[9] While this limits our capacity to investigate the impact of other potentially important software technologies and algorithms on employment, it provides consistent and well defined information on investments in automation technology as demonstrated by the existing literature (Frey et al. 2018, Graetz & Michaels 2018, Acemoglu & Restrepo 2020).

Based on IFR's industrial classification, within the manufacturing sector, we aggregate the operational stock of robots into twelve industries: food and beverages; textiles (including apparel); wood and furniture; paper and printing; plastic and chemicals; minerals, glass, and ceramics; basic metals and metal products; industrial machinery; electronics; automotive; other transport equipment; other manufacturing. Outside the manufacturing

[9] However, if some countries, like Japan, have their own surveys or calculations of the operational robot stock, the IFR uses those figures.

sector, we similarly group the data into six broad non-manufacturing industries: agriculture, forestry, and fishing; mining; utilities; construction; education, research and development; services. However, some robots are unspecified in the IFR dataset, which we assign following the existing literature.[10]

Figure I of the Online Appendix plots the trend of the operational stock of robots per thousand workers in the UK, Germany, as well as the average for Denmark, Finland, France, Italy, and Sweden. The UK robot stock starts around 0.34 robots per thousand workers in 1993 and increases rapidly to 0.6 in 2007. Thereafter, it rises gradually to 0.66 robots per thousand workers in 2015. We note that while there has been a secular increase in robot adoption in the UK, it has been consistently 50 to 70 percent lower than the adoption rates we observe in Denmark, Finland, France, Italy, and Sweden. As noted, this makes the UK a particularly interesting case to study, since robots might be subject to diminishing productivity returns.

We next match the IFR data to the number of employees from EUKLEMS ((van Ark & Jager 2017)) at the industry-country level. In line with what has become the standard approach in the literature (Acemoglu & Restrepo 2020, Dauth et al. 2021), we construct the UK adjusted penetration of robots (APR) at the industry level for the years 1993 to 2007. The APR is calculated as follows:[11]

$$APR^{UK}_{i,(1993,2007)} = \frac{\Delta R^{UK}_{i,(1993,2007)}}{L^{UK}_{i1990}}, \tag{1}$$

[10] Following Acemoglu & Restrepo (2020), we assign unspecified robots to each industry in the proportions that the remainder of the robot stock is allocated in each year. Robots for Denmark between 1993-1996 are allocated manually using the 1996 industry composition.

[11] Using the EUKLEMS dataset (November 2009 Release, updated March 2011), we can match most data to the 18 IFR industries. Since employees in furniture products are pooled with other manufacturing in the EUKLEMS, we allocated 60 percent of the employees in other manufacturing to the woods and furniture industry based on the share of employees in the UK furniture industry, using detailed industry employment surveys.

where $\Delta R^{UK}_{i,(1993,2007)}$ is the change in the number of robots in industry i between 1993 and 2007, and $L^{UK}_{i,1990}$ is the baseline employee level (per thousand workers) in industry i in 1990. As in Graetz & Michaels (2018), our analysis ends in 2007 to prevent potential bias from the confounding effects of the Great Recession and later uncertainty surrounding Brexit.

The main concern with model (1) is that robot adoption at the industry level could have been affected by local demand shocks. Thus, we proxy domestic penetration with the average penetration in five European countries that are ahead in terms of robotization relative to the UK. We interpret this variable as reflecting the existing *automation possibilities frontier*.[12] Specifically, we focus on Denmark, Finland, France, Italy, and Sweden ($EURO5$), because they are the countries with the highest penetration in Europe, with the exception of Germany, which is an extreme outlier (see Figure I of the Online Appendix).[13] Thus, the adjusted penetration of robots is calculated as follows:

$$\overline{APR}_{i,(1993,2007)} = \frac{1}{5} \sum_{j \in EURO5} \left[\frac{\Delta R^{j}_{i,(1993,2007)}}{L^{j}_{i1990}} \right], \tag{2}$$

where $\Delta R^{j}_{i,(1993,2007)}$ is the change in the number of robots in industry i in country j between 1993 and 2007, and $L^{j}_{i,1990}$ is the baseline employee level (per thousand workers) in industry i in country j in 1990. As discussed in greater detail in the below, the correlation between the two APR measures, UK and $EURO5$, is strong and equal to 0.87.

[12] See also Acemoglu & Restrepo (2020).

[13] We also experiment with different $\overline{APR_i}$ measures where we use Germany and $EURO5$ or Germany, Spain, and $EURO5$. The two measures are positively and highly correlated with EURO5 (corr=0.99 and 0.98, respectively).

2.2 Measuring the exposure to Chinese imports

Our measure of exposure to import competition from China is the change in the per thousand US dollar Chinese imports in each industry (Autor et al. 2013). The main trade data source in our analysis is the widely used UN Comtrade database, which provides import and export data at the six-digit Harmonized System (HS) level by trading partners and year.[14]

We begin by mapping the commodities in the Comtrade database to three-digit SIC industries, using the HS1992-SIC crosswalk provided by Autor et al. (2013). We then aggregate the SIC manufacturing industries to their 12 IFR manufacturing counterparts to have a measure that is comparable to our robot exposure variable. Figure II of the Online Appendix shows the share of UK imports from key countries between 1993 and 2018. In the 1990s, goods and services from China only accounted for 1 percent of total UK imports. After China joined World Trade Organization (WTO) in 2001, the share increased rapidly, reaching around 8 percent in 2007. Over the same period, German imports remained flat, while the share of imports from other important markets like the US, Japan, and South Korea declined. In other words, the UK has seen a marked shift in the composition of its imports away from the US, Japan and Korea in favor of Chinese inputs.

In terms of measurement, we define our adjusted import penetration (AIP) variable similarly to our variable for robot penetration:

$$AIP^{China-UK}_{i,(1993,2007)} = \frac{\Delta M^{China-UK}_{i,(1993,2007)}}{L^{UK}_{i1991}} \tag{3}$$

where $\Delta M^{China-UK}_{i,(1993,2007)}$ is the observed change in UK imports per thousand US dollars (2007=100) from China in industry i between 1993 and 2007. The denominator L^{UK}_{i1991}, is the to-

[14] Due to lags in adopting the HS classification, trade data between the UK and China is only available from 1993 onward, and hence this is the first year used for the UK and other high-income countries (as opposed to 1991).

tal number of employees in industry i in 1991. As with robots, the concern with model (3) is that it might be correlated to unobserved shocks. Therefore, we construct an instrumental variable to account for the potential endogeneity of the exposure to Chinese imports. We interpret this variable as proxying for the supply-driven component of imports from China, which should be unrelated to domestic UK conditions. Specifically, like Autor et al. (2013), we select eight typical high-income countries with strong Chinese import growth: Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland ($HIC8$).[15] Formally, our instrument is defined as:

$$\overline{AIP}_{i,(1993,2007)} = \frac{1}{8} \sum_{j \in HIC8} \left[\frac{\Delta M^{China-j}_{i,(1993,2007)}}{L^{UK}_{i1991}} \right] \tag{4}$$

where $\Delta M^{China-j}_{i,(1993,2007)}$ is the observed change in Chinese imports per thousand US dollars (2007=100) of country j in industry i during the period 1993 to 2007. We also replace the base-year employment level by city and industry with the respective value from the prior decade. This mitigates the concern of potential simultaneity bias resulting from anticipated trade growth.[16] We note that the UK-based measures of exposure to Chinese imports is highly correlated with the instrument (corr=0.776, weighted by city population in 1991).

2.3 Additional covariates

Further demographic information for each city is taken from the 1981 and 1991 Census, collected from UK NOMIS and Scotland's Census.[17] These variables include the log of population, the male population share, the foreign born population share, as well as the shares of Whites, Blacks, and Asians. We also include the share of the population aged 65

[15] We also experiment with an alternative measure where European countries are excluded. The two measures are positively and highly correlated (corr=0.998, weighted by city population in 1991).

[16] Recall that the earliest year of industry employee data is 1984.

[17] 2007 population data is collected from NOMIS: Population Estimates/Projections, which is based on the UK Census. Also, we map Scotland's local authorities in the 1981 and 1991 version to the April 2015 version.

or above as well as the share of the population with a higher degree qualification.[18]

As the pre-existing industrial structure could have confounding effects on local labor markets, we further include a set of city level industrial variables to ensure that our exposure variables do not work as proxies for other trends associated with general changes in employment. For example, Chinese import competition has proportionally large impacts on light manufacturing industries, which are also easy to outsource. Our industry variables are collected from the UK Business Register and Employment Survey in 1984 and 1991, and include the share of employment in light manufacturing, mining, and construction, as well as the share of female workers in manufacturing.[19] Finally, we control for the share of routine employment which could also affect the change in employment during this period.[20]

2.4 City-level descriptive statistics

Following Faggio & Overman (2014) and Becker et al. (2017), our analysis focuses on 352 local authority district areas covering England, Scotland, and Wales.[21] We refer to these local authorities district areas as "cities" throughout the paper. Table 1 provides some descriptive statistics indicating how cities with high and low exposure to robots or imports from China differ along a range of local labor market characteristics. Columns

[18]In the 1991 Census, a qualification is defined as having a higher degree or diploma. Data is from the Local Base Statistics 10% sample, and restricted to the population aged 18 and above.

[19]Foods, textiles, and paper and printing are classified as light manufacturing.

[20]In the UK 1991 Census, occupational employment is collected from Local Base Statistics 10% sample, aged 16 and over. As Jaimovich & Siu (2020), we define routine jobs as those occupations in administrative and secretarial, skilled trades, sales and customer service, process, plant and machine operatives, and the elementary category.

[21]The main disadvantage of local authorities as a measure of local labor markets is that they are not an enclosed area to approximate to a local labor market. For example, the Greater London area consists of 32 local authority districts (boroughs) where people work and reside in different boroughs. Since commuting patterns have kept changing, we merged boroughs on the NUTS 3 level (2003 version) to mitigate such concerns. We exclude Northern Ireland as its local market is geographically much closer to Ireland than other UK regions.

2–5 and 6-9 present the mean for outcomes and control variables by quartiles of exposure to robots and Chinese imports respectively. Notably, for both measures, more exposed cities experienced lower employment growth between 1991 and 2007, which is negative for manufacturing industries. Beyond employment trends, we do not find any substantial systematic difference for the base-year covariates considered. Nevertheless, further below we examine potential confounders in greater detail.

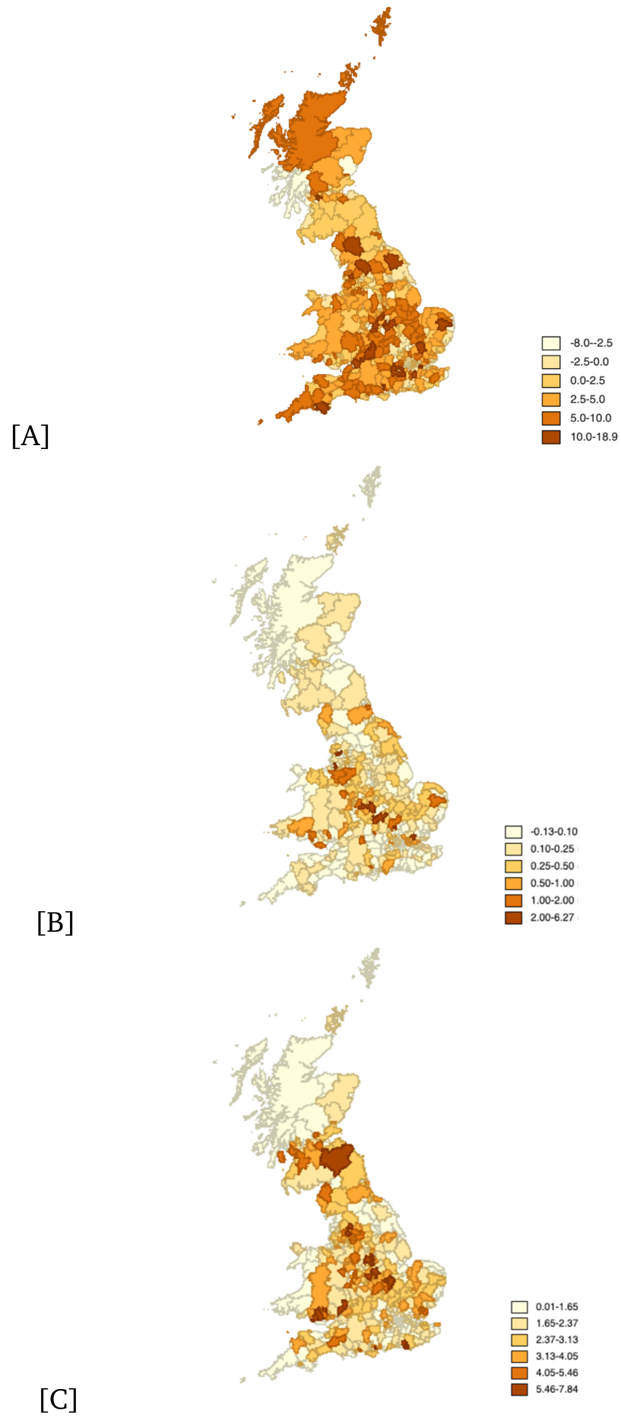
We further note that there is substantial variation in both employment changes (Panel A of Figure 2), and exposure to robots and Chinese imports across UK cities. Panel B of Figure 2 presents the spatial distribution of exposure to robots between 1993 and 2007 from equation (2). We find that the exposure to robots is less than 0.5 robots per thousand workers in most cities, while in some regions, including parts of North West, West Midland, and East of England, it ranges between 2 and 6 robots per thousand workers. We note that some of most exposed cities, like Coventry and Solihull, are specialized in automotive, which is the industry with the highest robot penetration. Finally, Panel C of Figure 2 highlights the distribution of exposure to Chinese import competition between 1993 and 2007 from equation (4). North East, North West, the West Midlands, and Wales are the regions most exposed to import competition from China. We note that Wales and the South West have considerable exposure to Chinese imports, but limited exposure to robots. We next turn to exploring how this variation has shaped employment patterns in the UK.

Table 1: Summary statistics.

		Means by quartiles of exposure to robots				Means by quartiles of exposure to Chinese imports			
	All cities	First quartile	Second quartile	Third quartile	Fourth quartile	First quartile	Second quartile	Third quartile	Fourth quartile
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Outcome variables									
Change employment to population ratio, 1991-2007	2.17	2.24	1.92	3.24	1.42	2.85	2.60	1.79	1.45
Change manu. employment to population ratio, 1991-2007	-2.59	-1.65	-2.29	-2.77	-3.63	-1.40	-2.08	-2.89	-4.04
Control variables (data for 1991)									
Log population	12.29	12.50	12.27	12.05	12.32	12.17	12.40	12.47	12.06
Female population share (%)	0.48	0.48	0.48	0.49	0.49	0.48	0.48	0.49	0.49
Population share (%) above 65	0.16	0.17	0.17	0.16	0.15	0.17	0.16	0.15	0.15
Asian population share (%)	0.03	0.03	0.04	0.02	0.04	0.02	0.03	0.04	0.04
Black population share (%)	0.02	0.03	0.01	0.01	0.01	0.01	0.03	0.02	0.01
White population share (%)	0.95	0.93	0.94	0.97	0.94	0.97	0.94	0.94	0.94
Population population share (%) with qualifications	0.12	0.14	0.13	0.11	0.10	0.13	0.12	0.12	0.10
Foreign born population share (%)	0.07	0.09	0.07	0.04	0.06	0.06	0.07	0.08	0.06
Employment share (%) in light manu.	0.33	0.43	0.35	0.32	0.24	0.42	0.35	0.30	0.26
Employment share (%) in construction	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Employment share (%) in mining	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Female employment share (%) in manu.	0.30	0.32	0.31	0.31	0.28	0.31	0.30	0.30	0.30
Employment share (%) in routine jobs	0.42	0.39	0.40	0.42	0.44	0.40	0.41	0.42	0.43

Notes: Columns 1 shows the sample means for all cities. Column 2-5 present means by quartiles of exposure to robots from equation (2), while column 6-9 show the exposure to Chinese imports from equation (4). The means are weighted by city population in 1991.

Figure 2: Geographic distribution of exposure to robots and Chinese imports, 1993-2007.



Source: UK NOMIS.

Notes: The maps show the spatial distribution of employment changes (panel A), exposure to robots (panel B), and the exposure to Chinese imports (panel C), over the period 1993 to 2007 across UK cities. The population-weighted correlation (population in 1991) between exposure to robots and the exposure to Chinese imports is 0.053.

3 Empirical Strategy

To study the impact of robots on jobs, we take advantage of the fact that there is substantial geographic variation in industry specialization, meaning that the impact of robots will vary across cities: local economies that have specialized in industries where more industrial robots are installed should be differentially affected by the uptake of robots across the UK economy. As we can not observe the exact use of robots across cities, we measure local exposure to robot (ER) using a shift-share method as in Acemoglu & Restrepo (2020), which combines the adjusted penetration of robots by industry with data on local industry employment:

$$ER_d = \sum_{i \in I} l_{di}^{1984} \cdot \overline{APR}_{i,(1993,2007)} \tag{5}$$

where $\overline{APR}_{i,(1993,2007)}$ is given in equation (2) and l_{di}^{1984} is the share of employment in industry i in city d. The employment share in 1984 captures the historical industrial specialization of cities *before* industrial robots were in use.[22] This allows us to mitigate any mechanical correlation related to changes in industry employment that are the result of the anticipation of the introduction of industrial robots in the late 1980s.

We compute exposure to Chinese imports at the local level (EM) analogously:

$$EM_d = \sum_{i \in I} l_{di}^{1984} \cdot \overline{AIP}_{i,(1993,2007)} \tag{6}$$

where $\Delta M_{i,(1993,2007)}^{China-other}$ is the observed change in the sum of other countries imports per thousand US dollars (2007=100) from China in industry i during the period between

[22]The earliest UK employment data at local authority district level is available from 1984. The city-industry employee data are collected from the 1984 Census of Employment employee analysis, the 1991 Annual Employment Survey employee analysis, and the 2001 and 2007 Annual Business Inquiry employee analysis. All such survey data are integrated and provided by UK NOMIS: Business Register and Employment Survey. The surveys provide information on job location and industry classifications.

1993 and 2007. We also replace the start-of-period employment level by industry and city with those from the prior decade to mitigate potential simultaneity bias, which may be the result from anticipated trade growth. The UK-based measures of exposure to Chinese imports is highly correlated to the instrument (corr=0.776, weighted by city population in 1991). Our baseline specification is an ordinary least squares (OLS) model:

$$Y_{d(1993,2007)} = \alpha + \beta_1 ER_d + \beta_2 EM_d + \boldsymbol{BX}'_{d1991} + \delta_r + e_d \tag{7}$$

where the outcome variable $Y_{d(1993,2007)}$ is the change in the employment-to-population ratio between 1991 and 2007 in city d. We note that the specification in long-differences absorbs all city-level time invariant characteristics. We also include a vector of UK NUTS2 regional dummies, δ_r, which is particularly useful to mitigate the potential confounding impact of immigration flows to broadly-defined labor markets. Finally, the vector $\boldsymbol{X}_{d1991}$ includes base-year covariates, like the change in the share of foreign-borns at the city-level, among several additional variables, which we discuss in the below. As noted, our analysis ends in 2007 to prevent potential bias from the confounding effects of the Great Recession and later uncertainty surrounding Brexit.[23]

3.1 Threats to validity

The crucial identifying assumption behind equation (7) is that cities where industries have witnessed the use of more robots or Chinese imports are not experiencing other shocks or trends affecting their labor markets. This sections examines potential threats to the validity of this identification strategy. To that end, Figure 3 explores whether robots and Chinese imports interact with other key variables across UK manufacturing industries, where the

[23] Similar to Acemoglu & Restrepo (2020), we rescale the outcome variables to a 14-year equivalent change to match the time period of exposure to robots and Chinese imports. The long-differences of outcome variables are constructed as $(y_{2007} - y_{2001}) + 0.8 \times (y_{2001} - y_{1991})$.

bulk of industrial robots and Chinese intermediate inputs are being used.[24] It reveals some noteworthy patterns. First, the industries that have adopted more industrial robots (automotive, plastic and chemicals) differ from those industries affected more by Chinese imports (electronics and textiles). This suggests that model (7) should in principle be able to disentangle the impact of the two shocks. Second, the industries most exposed to robots and Chinese imports are not disproportionately affected by capital deepening and other ICT equipment. This bolsters our assumption that our variables of interest are largely unrelated to other key drivers of structural change at the industry-level.

Moreover, as noted above, our main regressors are shift-share Bartik variables. Given that robots and Chinese inputs are concentrated in a few industries (Figure 3), the identification of the associated parameters should arise mainly from local differences in exposure to a few common shocks. Therefore, we follow Goldsmith-Pinkham et al. (2020) in computing Rotemberg weights, which quantify the relative importance of each industry in determining the overall explanatory power of the shift-share instrument. The Rotemberg weights are plotted in Figure IV of the online appendix. We find that a small number of industries carry a large share of the weight. Automotive, plastics and chemicals—which are the industries using most robots—explain 94 percent of the predictive power of the robot Bartik variable, while electronics and textiles explain 60 percent of the predictive power of the Chinese import instrument.[25]

Goldsmith-Pinkham et al. (2020) shows that identification under the Bartik-style approach is valid as long as the local share of the main industries (in terms of the Rotemberg weights) are uncorrelated to local factors that might affect the dependent variable—that

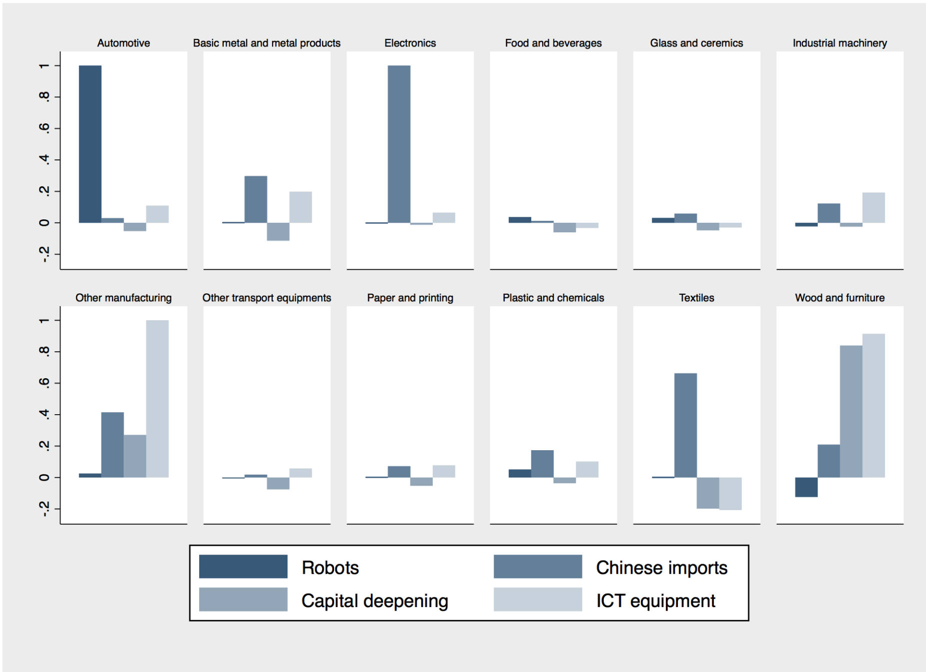
[24]To ease the comparison, for each industry, we normalize the indicator with the largest increase being equal to one.

[25]In a different context, Goldsmith-Pinkham et al. (2020) find that only 5 of the available 228 industries explain almost half of the predictive power of the Bartik variable. Hence, it is not surprising that in our sample with 18 and 12 industries for the robot and Chinese import instrument, respectively, only 2 industries drive most of their predictive power.

is, employment growth in our case. Thus, we probe the validity of our hypothesis by regressing the shares of the main industries on several base-year covariates that might affect changes in employment. We also include the city-level change in employment before the beginning of the period of analysis.[26] We do so in order to investigate whether exposure to robots and Chinese imports just pick up the variation of pre-exiting industry trends, like employment declines before the adoption of robotics technology. We address this by regressing the change in the employment-to-population ratio between 1984 and 1991, when industrial robots were rare and China was not yet integrated into the global economy, on our exposure variables as well as by controlling for other trends at the industry-city level. Specifically, Table I of the online appendix regresses the city-level industry shares, as well on the robot and Chinese import instruments, on several base-year covariates that might affect industry composition as and changes in employment. We find that some covariates enter the regression significantly (but not the pre-trends), and so we include them in $\boldsymbol{X}_{d1991}$ of regression model (7).

[26]Recall that 1984 is the earliest year for which we can collect industry employment data across cities.

Figure 3: Penetration of robots and Chinese imports: industry-level correlations with capital deepening and ICT equipment across UK manufacturing industries, 1993-2007.



Notes: This figure plots the adjusted penetration of robots between 1993 and 2007 as well as the change in Chinese imports, the growth in the total capital stock, and the growth in the ICT capital stock for 12 manufacturing industries.

4 Results

Table 2 presents our results from estimating equation (7). Since we are interested in the aggregate employment effects of robots and Chinese imports on the UK economy, we weight all estimates by city population in 1991.[27] Given that the regressors of interest vary at the NUTS3-level, standard errors are clustered accordingly. In column 1, the robots coefficient is negative and significant at the 99 percent confidence level. The magnitude of the coefficient implies that one robots per thousand workers reduces the employment-to-population ratio by 0.6 percentage points. In column 2, the coefficient of exposure to Chinese imports is also negative and significant: it implies that an increase of $1,000 imports from China per worker (in 2007 US dollars) in a given city reduces its employment-to-population ratio by 0.13 percentage points. In column 3, we include the key variables of interest together, whose coefficients remain both negative and significant, though slightly smaller in magnitude.

Despite the low robot uptake in the UK, their employment impact is still negative. Using the estimated coefficient in column 3, we can perform a back-of-the-envelope calculation as in Acemoglu & Restrepo (2020) and Dauth et al. (2021), which suggests that one industrial robot has been responsible for roughly 9 workers lost over the sample period.[28] IFR data shows that the UK added 3,592 robots over the sample period, which implies that robots have displaced 32,328 workers between 1991 and 2007. While such back-of-the-envelope calculations must always be taken with a pinch of salt, it does suggest that the impact of robots on overall employment in the UK has been small but non-negligible. We also perform similar calculations for Chinese imports for comparison. Our estimates imply

[27] This is the standard approach adopted by Acemoglu & Restrepo (2020) and Dauth et al. (2021), among others.

[28] One robot per thousand workers is equivalent to 0.56 robots per thousand persons in the United Kingdom. The estimated impact of one additional robots per thousand workers is -.52 percentage points. Therefore, $.0052/.56 \times 1000 = 9$.

that on average, \$1000 of Chinese imports displaced 0.002 workers. Over the sample period, Chinese imports increased by \$10,554,500, which implies that 21,109 workers were displaced as a consequence.

Finally, to further explore the relative importance of robots and Chinese imports in holding back employment growth, we calculate standardised coefficients. We find that one standard deviation increase in robot penetration reduces the employment-to-population ratio by .16 percentage points, while one standard deviation increase in Chinese imports reduces employment by .13 percentage points. Thus, similarly to the job losses calculated above, the standardised coefficients suggests that the impacts of trade and technology on jobs in the UK have been qualitatively and quantitatively similar.

Table 2: The impact of robots and Chinese imports on the UK employment-to-population ratio: baseline reduced-form results.

	(1) Emp-pop ratio	(2) Emp-pop ratio	(3) Emp-pop ratio
Exposure to robots (instrument)	-0.620***		-0.518**
	(0.210)		(0.215)
Exposure to Chinese import (instrument)		-0.134***	-0.107**
		(0.050)	(0.052)
Observations	352	352	352
R-squared	0.429	0.427	0.437
Region FE	yes	yes	yes
Base-year covariates	yes	yes	yes

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese imports in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

4.1 Robustness

In this section, we perform a battery of robustness checks to probe the main results of Table 2. As shown in Section 3.1, exposure to robots and Chinese imports in the automotive and electronics industries respectively, drive most of the explanatory power of the shift-share instruments. This raises concerns that our estimates may be confounded with other changes affecting these particular industries. As is customary in the literature (e.g. Goldsmith-Pinkham et al. 2020), we address these concerns by regressing employment changes on exposure to robots and Chinese imports excluding the automotive and electronics industries, respectively. The results are presented in Table II of the Online Appendix. Reassuringly, the coefficients of all variables are still negative and statistically significant.

Second, we check that our results do not depend on the time period under consideration. To that end, we run the specification in long differences but for the years 1993 to 2015, which inevitably means that we consider the period of the Great Recession as well as the years leading up to Brexit. The results are presented in Table III of the Online Appendix. The coefficients are smaller than in our baseline specification, but the results are qualitatively identical when we consider also the post-Great Recession period.

Third, robots and imports from China are not the only forces affecting employment in the UK. In particular, we are concerned that our results might be capturing the impact of ICT technology or capital deepening more broadly, or other shocks related to globalization. As discussed in Section 3.1, this might be particularly problematic if such shocks are also correlated to the local shares of employment used to construct the exposure variables. To mitigate such concerns, we construct additional Bartik-style variables to capture broader technological and trade-related trends, and check that their inclusion as control variables does not change our main results. Doing so, we begin by considering technological trends. Specifically, we compute the Bartik measures aggregating changes in the aggregate stock of capital and ICT capital from EUKLEM, with our base-year employment shares. Our results are presented in Table IV of the Online Appendix. While the impact of robots remains significant and negative, our Chinese imports variable does not, suggesting that Chinese import penetration may not impact employment *per se*. It might, for example, also reflect changes in technology adoption by UK firms. Such an interpretation would be consistent with the evidence from Artuc et al. (2020), which shows that the adoption of automation technologies increases imports. Still, it would be misleading to conclude that Chinese import penetration has not played a role in determining employment trends in the UK. For instance, the coefficients of capital deepening and ICT capital in Table IV are not statistically significant, suggesting that their impacts on *aggregate* employment trends have been negligible, though this is not the case for manufacturing employment: as shown in Table V of the Online Appendix, capital deepening in the manufacturing sector is associated with an increase in the employment-to-population ratio.[29] We also note that the coefficient of ICT capital has a negative sign, but is not statistically significant. More importantly, in our context, the impact of Chinese imports on manufacturing employment is still negative and significant, even when controlling for capital deepening.

We next turn to controlling for globalization-related shocks. We begin by computing three Bartik measures aggregating changes in: i) imports from countries other than China; ii) exports to China; and iii) exports to countries other than China, with our base-year employment shares. All trade data are taken from the UN Comtrade database. In addition, we add an intensity index of local FDI inflows (from all countries) based on OECD data.[30] This variable, however, is only available for the years 2008 to 2015. Therefore, we ag-

[29] This is consistent with standard economic theory, which predicts that an increase in the capital stock increases the marginal product of labor.

[30] The FDI data can be accessed from the database "FDI by country and economic activity_BMD4 and historical BMD3 series" at https://stats.oecd.org/#.

gregate industry average FDI over all years using base-year employment shares.[31] Finally, we construct a measure of offshorability by mapping the offshorability index of Goos et al. (2014) onto occupational categories in the UK 1991 census.[32] To aggregate the index at the city-level, we use the employment weights by occupation within a city. This variable, as expected, is substantially correlated to the local share of routine employment (correlation coeff. = 0.65). Hence, to avoid introducing multicollinearity, we generate a dummy variable equal to 1 if a city has an offshorability index larger than the 75th percentile of the index sample distribution.[33]

Our results are presented in Table VI of the Online Appendix. We note that in column 1, the coefficient of exposure to robots turns statistically insignificant. We further note that this is due to a doubling of the standard errors, rather than a reduction in the coefficient. This implies a substantial degree of collinearity between the additional controls and the main regressor of interest. In columns 2 and 3, on the other hand, all coefficients of interest are at least as large as in the baseline specification, and still statistically significant. As expected, we find a positive impact of exports to China, while the impact of imports from countries other than China is negative, large and significant across all specifications. And despite this, our imports from China variable remains statistically significant. We also find that FDI intensity tends to have a positive impact on employment, consistent with the view that investment by multinationals' creates jobs. Finally, we note that the offshorability index has a negative coefficient, though it is not statistically significant.

Overall, this evidence reassures us that our results are not driven by shocks related to technology and globalization other than the exposure to robots and imports from China.

[31] While we prefer to use the time-average to avoid picking up the impact of the Great Recession, we obtain very similar results if we use the FDI inflow in 2008.

[32] Goos et al. (2014) uses the methodology of Blinder & Krueger (2013), which is based on the United States, to calculate the offshorability by different occupation in Europe.

[33] Results are similar if we take other thresholds to construct the dummy variable.

4.2 Diminishing Returns to Automation

The results of Table 7 suggest that despite the overall low levels of domestic penetration of robots and Chinese imports, automation has had a substantial negative impact on employment in the United Kingdom, even somewhat larger in magnitude than observed by Acemoglu & Restrepo (2020) for the United States. We note that this runs counter to the prediction of the task-based model, which suggests that places with lower initial penetration of automation technologies should see a larger productivity effect and a lower displacement effect. One plausible explanation is that while the displacement effect is geographically concentrated, the countervailing productivity effect might be more dispersed, and is thus not fully captured in our estimates. This is particularly likely in a country like the United Kingdom, where the investment activity of foreign firms' is double the OECD average and almost three times larger than in the United States (Online Appendix Figure III).[34]

To shed light on whether the diminishing productivity returns to automation prediction of the task model holds *within* the United Kingdom, which is the focus of this paper, we proceed as follows. We begin by computing the initial exposure to robots and Chinese imports for each city, respectively, as follows:

$$DPR_d = \sum_{i \in I} l_{di}^{1984} \cdot \frac{R_{i,1993}^{UK}}{L_{i,1990}^{UK}}$$

$$DPM_d = \sum_{i \in I} l_{di}^{1984} \cdot \frac{M_{i,1993}^{UK}}{L_{i,1991}^{UK}}$$

Second, we construct variables equal to 1 if a city's initial exposure is larger than different percentile thresholds of the distributions of the two variables. Finally, we include

[34]The figure is based on the years 2005-2006—the only two years with data pre-dating the end of our sample period.

these dummies and their interaction with ER_d and EM_d in model (7) and estimate the parameters using OLS. Our results are presented in Table 3, which reports the interaction coefficients of interest, as well as the sum of the main exposure variable and the interaction, which corresponds to the estimated impact of exposure in cities with high initial penetration. We note that the interaction coefficients tend to be negative, which is consistent with the idea that automation reduces employment more in cities with high initial exposure, as predicted by the task model of Appendix A. However, the estimated impact of robots in columns 1 and 2 are not statistically significant at conventional levels, and in columns 4 and 5 the interaction coefficients are positive. Though the main effect of exposure is not significant, suggesting that in cities with low-initial penetration, robots did not have a significant impact on employment, the impact becomes negative and significant in cities with initial exposure larger than the 25th or 10th percentile. Turning to the impacts of Chinese imports, we note that the evidence on diminishing returns is more robust (columns 6 to 10). The negative impact of Chinese imports on employment is consistently larger in cities with high initial exposure for all specifications considered. One possible explanation for the higher precision of these estimates—relative to the impact of robots—is that the initial exposure to Chinese imports is much more dispersed across cities than robot exposure, thus providing a larger source of variation to identify the parameters.[35] This feature of the data, together with the fact that the productivity effect might be more geographically dispersed than the displacement effect, are likely to explain why the evidence of diminishing returns to automation is mixed.

[35]The standard deviation of (log) initial exposure Chinese imports is 1.06 and .7 for robots.

Table 3: Decreasing returns to automation.

	(1) Emp-pop ratio	(2) Emp-pop ratio	(3) Emp-pop ratio	(4) Emp-pop ratio	(5) Emp-pop ratio	(6) Emp-pop ratio	(7) Emp-pop ratio	(8) Emp-pop ratio	(9) Emp-pop ratio	(10) Emp-pop ratio
Exposure to robots	-0.872***	-0.245	-0.300	-3.162	-3.572					
	(0.323)	(0.776)	(0.904)	(2.155)	(3.983)					
Exposure to robots X high initial exposure (p90)	-0.195									
	(0.746)									
Sum of coefficients	-1.068									
	(0.663)									
Exposure to robots X high initial exposure (p75)		-0.059								
		(0.787)								
Sum of coefficients		-0.304								
		(0.220)								
Exposure to robots X high initial exposure (mean)			-0.205							
			(0.930)							
Sum of coefficients			-0.505**							
			(0.239)							
Exposure to robots X high initial exposure (p25)				2.551						
				(2.152)						
Sum of coefficients				-0.611***						
				(0.226)						
Exposure to robots X high initial exposure (p10)					2.971					
					(3.991)					
Sum of coefficients					-0.601***					
					(0.217)					
Exposure to Chinese imports						-0.145***	-0.073	-0.072	-0.057	0.594**
						(0.049)	(0.061)	(0.068)	(0.120)	(0.261)
Exposure to Chinese imports X high initial exposure (p90)						-1.348***				
						(0.283)				
Sum of coefficients						-1.493***				
						(0.295)				
Exposure to Chinese imports X high initial exposure (p75)							-0.163			
							(0.107)			
Sum of coefficients							-0.236**			
							(0.094)			
Exposure to Chinese imports X high initial exposure (mean)								-0.110		
								(0.107)		
Sum of coefficients								-0.181**		
								(0.087)		
Exposure to Chinese imports X high initial exposure (p25)									-0.064	
									(0.121)	
Sum of coefficients									-0.121**	
									(0.060)	
Exposure to Chinese imports X high initial exposure (p10)										-0.721***
										(0.256)
Sum of coefficients										-0.127**
										(0.055)
Observations	352	352	352	352	352	352	352	352	352	352
R-squared	0.439	0.443	0.436	0.437	0.435	0.479	0.438	0.436	0.433	0.439
Region FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Base-year covariates	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese imports in eight high-income countries as in Autor et al. (2015). High initial exposure is a dummy equal to 1 if a city has initial exposure larger than the respective percentile of the sample distribution. The table omits the estimated dummies for exposition purposes and presents the interaction coefficients only. Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

4.3 The Brexit Effect

Finally, we turn to exploring the popular perception that automation and globalization are key forces behind the popular support for leaving the European Union. Indeed, Autor et al. (2020) show that Chinese imports contributed to the election of Donald Trump, while Frey et al. (2018) document that robots shaped the outcome of the 2016 US presidential election. In addition, Colantone & Stanig (2019) find that places with greater exposure to robots in Europe were also more likely to opt for populists. Finally, in the UK context, Becker et al. (2017) show that the Brexit vote was driven by fundamental factors, such as historical dependence on manufacturing employment, low incomes, and high unemployment—factors that in turn have been driven by automation and globalization, at least in part.

To probe how robot adoption and Chinese import competition shaped the outcome of the 2016 EU referendum, we regress the vote share for Leave by city on exposure to robots and Chinese imports, over the years 1993 to 2015.[36] Table 4 presents the results and shows that none of the coefficients are statistically significant. In other words, we do not find much support for the hypothesis that robots and imports from China are associated with greater support for Vote Leave. This is not surprising, since as already noted, Britain has among the lowest robot and Chinese import penetration in the OECD.[37] Indeed, IFR data shows that the UK economy only added 6,482 robots over the full sample, which implies that robots displaced 58,338 workers between 1991 and 2015.

[36] The data are available at `https://www.data.gov.uk/dataset/be2f2aec-11d8-4bfe-9800-649e5b8ec044/eu-referendum-results`.

[37] We note that Colantone & Stanig (2018), find a positive relationship between Chinese imports and Vote Leave support. The main difference of our setup is that we control for a more granular region fixed effects (NUTS2-level instead of NUTS1), and include the control variables discussed in Section 3.1, which are needed to minimize the concern over violating our identification assumptions. We are able to obtain similar results if we mimic their specification, as shown in Online Appendix Table VII.

Table 4: The impact of robots and Chinese imports on the 2016 EU referendum.

	(1) Share of Vote Leave	(2) Share of Vote Leave	(3) Share of Vote Leave
Exposure to robots (1993-2015)	-0.019		-0.047
	(0.206)		(0.214)
Exposure to Chinese import (1993-2015)		0.027	0.028
		(0.048)	(0.049)
Observations	347	347	347
R-squared	0.841	0.841	0.841
Region FE	yes	yes	yes
Full set of base-year covariates	yes	yes	yes

Notes: This table presents OLS estimates of the relationship between the share of votes in favor of Brexit and exposure to robots and Chinese imports over the years 1993 to 2015. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese imports in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

5 Conclusions

Technology and trade are widely regarded two of the prime forces shaping labor markets across the industrial world. Robots have been put into widespread use over the past three decades, and they are expected to spread even more rapidly in the decades to come (BCG 2015). However, despite the recent acceleration in robot penetration, the impacts of automation on jobs are still being debated (Autor 2015, Bessen 2015, Frey 2019, Ford 2015). For example, in the US context, it has been suggested that automation merely has led to job polarization, while import competition from China has been the more important driver of unemployment and non-employment (Autor et al. 2015).

In this paper, we disentangle the impacts of technology and trade on local labor markets in the United Kingdom between 1991 and 2007. Our findings show that both forces have shaped the fortunes of cities across England, Scotland, and Wales over this period. Specifically, we find that while the use of industrial robots is largely uncorrelated with cities exposure to trade competition from China, they have affected employment in similar ways. Our baseline estimate suggests that one more robot per thousand workers reduced the employment-to-population ratio by 0.5 percentage points, while an increase of $1,000 imports from China per worker reduced the employment-to-population ratio by 0.11 percentage points on average. We also show that although these effects are clearly sizable, low penetration rates mean that they did not have any significant impacts on Britain's decision to leave the EU.

That said, the spread of robots, software, and AI is widely expected to accelerate in the next decades (Brynjolfsson & McAfee 2011, Frey & Osborne 2017), which could make the employment impacts of technology even more sizable. In addition, it has been argued that technologies like telepresence and telerobotics will usher another wave of offshoring (Baldwin 2016). Thus, going forward, the effects of globalization and automation on employment are expected to grow stronger in the industrial world.

Still, there is no reason to think that the impacts of trade and technology on jobs must be uniform over time and space. We already see that this is not the case. For example, while both robots and Chinese imports have reduced employment in the US, results for the German economy differ quite substantially: Chinese imports only had negligible job displacement effects and manufacturing job losses due to robots were offset by gains in other sectors (Dauth et al. 2019). Meanwhile, in France, robots as well as Chinese imports are shown to have reduced employment (Acemoglu & Restrepo 2020, Malgouyres 2017). And in Norway, the impacts of Chinese imports on jobs and wages have been negative and significant, though the effects are much smaller compared to those observed in the US (Balsvik et al. 2015). We add to this literature by showing that the employment impacts of robots and Chinese imports in the UK are similar to the effects observed in the US. Hence, our findings speak to the notion that the institutions of Anglo-American capitalism yield similar labor market outcomes, which might help explain why wage inequality in the UK and the US has grown particularly rapidly since the 1980s. The interaction between automation, globalization, and institutions in shaping labor market outcomes is a line of inquiry that deserves further attention.

Finally, we provide some suggestive evidence that the impact of automation has not been uniform across cities in the United Kingdom. Overall, our estimates suggest that cities with high initial penetration of robots and Chinese imports tend to experience larger employment declines as automation progresses. We interpret this finding through the lens of the task-based model, which suggests the productivity gains are more limited and labor displacement higher when there are only few opportunities left for automation, though we note that the evidence in favour of this hypothesis is somewhat mixed. We deem a deeper examination of this issue to be a fruitful area for future research.

References

Acemoglu, D., Lelarge, C. & Restrepo, P. (2020), Competing with robots: Firm-level evidence from france, *in* 'AEA Papers and Proceedings', Vol. 110, pp. 383–88.

Acemoglu, D. & Restrepo, P. (2018), 'The race between man and machine: Implications of technology for growth, factor shares, and employment', *American Economic Review* **108**(6), 1488–1542.

Acemoglu, D. & Restrepo, P. (2020), 'Robots and jobs: Evidence from us labor markets', *Journal of Political Economy* **128**(6), 2188–2244.

Acemoglu, D. & Robinson, J. A. (2013), *Why nations fail: The origins of power, prosperity, and poverty*, Crown Business.

Aghion, P., Antonin, C., Bunel, S. & Jaravel, X. (2020), 'What are the labor and product market effects of automation? new evidence from france'.

Artuc, E., Bastos, P. & Rijkers, B. (2020), 'Robots, tasks, and trade', *CEPR Discussion Paper No. DP14487* .

Autor, D., Dorn, D. & Hanson, G. (2015), 'Untangling trade and technology: Evidence from local labour markets', *Economic Journal* (584), 621–646.

Autor, D., Dorn, D. & Hanson, G. (2016), 'The china shock: Learning from labor-market adjustment to large changes in trade', *Annual Review of Economics* **8**(1), 205–240.

Autor, D., Dorn, D., Hanson, G. & Majlesi, K. (2020), 'A note on the effect of rising trade exposure on the 2016 presidential election: In appendix to "importing political polarization"', *American Economic Review* **110**(10), 3139–83.

Autor, D. H. (2015), 'Why are there still so many jobs? the history and future of workplace automation', *Journal of Economic Perspectives* **29**(3), 3–30.

Autor, David, H., Dorn, D. & Hanson, G. H. (2013), 'The China syndrome: Local labor market effects of import competition in the United States', *American Economic Review* **103**(6), 2121–2168.

Baldwin, R. (2016), *The Great Convergence*, Harvard University Press.

Baldwin, R. (2019), *The Globotics Upheaval: Globalization, Robotics, and the Future of Work*, Oxford University Press.

Balsvik, R., Jensen, S. & Salvanes, K. G. (2015), 'Made in china, sold in norway: Local labor market effects of an import shock', *Journal of Public Economics* **127**, 137–144.

BCG (2015), The robotics revolution: The next great leap in manufacturing, Tech. report, Boston Consulting Group.

Becker, S. O., Fetzer, T. & Novy, D. (2017), 'Who voted for Brexit? A comprehensive district-level analysis', *Economic Policy* **32**(92), 601–650.

Belloc, F., Burdin, G. & Landini, F. (2020), 'Robots and worker voice: An empirical exploration'.

Bessen, J. (2015), *Learning by doing: the real connection between innovation, wages, and wealth*, Yale University Press.

Bessen, J., Goos, M., Salomons, A. & van den Berge, W. (2020), 'Firm-level automation: Evidence from the netherlands', *AEA Papers and Proceedings* **110**, 389–93.

Blinder, A. S. & Krueger, A. B. (2013), 'Alternative measures of offshorability: a survey approach', *Journal of Labor Economics* **31**(S1), S97–S128.

Bonfiglioli, A., Crinò, R., Fadinger, H. & Gancia, G. (2020), 'Robot imports and firm-level outcomes'.

Brynjolfsson, E. & McAfee, A. (2011), 'Race against the machine: How the digital revolution is accelerating innovation, driving productivity, and irreversibly transforming employment and the economy'.

Brynjolfsson, E. & McAfee, A. (2014), *The Second Machine Age: Work, Progress, and Prosperity in a Time of Brilliant Technologies*, WW Norton & Company.

Calì, M. & Presidente, G. (2022), 'Robots for economic development', *Kiel, Hamburg: ZBW-Leibniz Information Centre for Economics* .

Colantone, I. & Stanig, P. (2018), 'Global competition and brexit', *American political science review* **112**(2), 201–218.

Colantone, I. & Stanig, P. (2019), 'The surge of economic nationalism in western europe', *Journal of Economic Perspectives* **33**(4), 128–51.

Dauth, W., Findeisen, S., Suedekum, J. & Woessner, N. (2019), 'The adjustment of labor markets to robots', *Journal of the European Economic Association* .

Dauth, W., Findeisen, S., Suedekum, J. & Woessner, N. (2021), 'The adjustment of labor markets to robots', *Journal of the European Economic Association* **19**(6), 3104–3153.

Dottori, D. (2020), Robots and employment: evidence from italy, Occasional Papers 572, Bank of Italy, Economic Research and International Relations Area.

Faggio, G. & Overman, H. (2014), 'The effect of public sector employment on local labour markets', *Journal of Urban Economics* **79**(C), 91–107.

Foliano, F. & Riley, R. (2017), 'International trade and uk de-industrialisation', *National Institute Economic Review* **242**(1), R3–R13.

Ford, M. (2015), *Rise of the Robots: Technology and the Threat of a Jobless Future*, Basic Books.

Frey, C. (2019), *The Technology Trap: Capital, Labor, and Power in the Age of Automation*, Princeton University Press.

Frey, C. B., Berger, T. & Chen, C. (2018), 'Political machinery: did robots swing the 2016 US presidential election?', *Oxford Review of Economic Policy* **34**(3), 418–442.

Frey, C. B. & Osborne, M. A. (2017), 'The future of employment: How susceptible are jobs to computerisation?', *Technological forecasting and social change* **114**, 254–280.

Goldsmith-Pinkham, P., Sorkin, I. & Swift, H. (2020), 'Bartik instruments: What, when, why, and how', *American Economic Review* **110**(8), 2586–2624.

Goos, M., Manning, A. & Salomons, A. (2014), 'Explaining job polarization: Routine-biased technological change and offshoring', *American economic review* **104**(8), 2509–26.

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

Hall, P. A. & Soskice, D. (2001), 'An introduction to varieties of capitalism', *Oxford University Press* pp. 21–27.

IFR (2014), World robotics: Industrial robots, Tech. report, International Federation of Robotics, Frankfurt, Germany.

Jaimovich, N. & Siu, H. (2020), 'Job polarization and jobless recoveries', *The Review of Economics and Statistics* **102**(1), 129–147.

Malgouyres, C. (2017), 'The impact of chinese import competition on the local structure of employment and wages: Evidence from france', *Journal of Regional Science* **57**(3), 411–441.

Presidente, G. (2021), Institutions, holdup and automation, Technical report, Oxford Martin Working Paper Series on Economic and Technological Change No. 2020-5.

Thelen, K. (2001), 'Varieties of labor politics in the developed democracies', *Varieties of capitalism: The institutional foundations of comparative advantage* **71**, 76–92.

Thelen, K. (2014), *Varieties of Liberalization and the New Politics of Social Solidarity*, Cambridge Studies in Comparative Politics, Cambridge University Press.

van Ark, B. & Jager, K. (2017), 'Recent trends in europe's output and productivity growth performance at the sector level, 2002-2015', *International Productivity Monitor* **33**, 8–23.

Online Appendix (not for publication)

A A Task Model

Consider a representative firm producing a final good by combining a continuum of varieties of total measure 1. Varieties are produced by an intermediate good-producing firm f:

$$Y = \left[\int_0^1 y_f^{\frac{\sigma-1}{\sigma}} df \right]^{\frac{\sigma}{\sigma-1}}$$

with $\sigma > 1$.

The price of the final good is normalised to $P \equiv 1$. Each firm then faces a constant elasticity demand function:

$$y_f = p_f^{-\sigma}$$

Varieties are produced combining a unit measure of tasks, each indexed by z, with the production function

$$y_f = \exp\left(\int_0^1 \ln x_f(z) dz \right)$$

The variable $x_f(z)$ represents the quantity of task z demanded by the firm. All firms are identical and face the same problem, so that we can suppress f subscripts.

Tasks can be performed by human workers or machines with the following task production functions:

$$x(z) = \begin{cases} \gamma(z) \cdot n(z) & \text{if performed with labor} \\ \eta(z) \cdot k(z) & \text{if performed with capital} \end{cases} \tag{8}$$

where $n(z)$ and $k(z)$ are labor and capital allocated by the firm to the production of task z. Labor and capital are fully flexible across tasks and firms.

The ratio $\gamma(z)/\eta(z) \equiv \tilde{\gamma}(z)$ represents the comparative advantage of human labor over machines in performing task z. Following Acemoglu & Restrepo (2018) we assume, without loss of generality, that that $\tilde{\gamma}(z)$ is increasing in z, so that higher-ordered tasks are more costly to automate.

The firm-level extent of automation is summarised by the parameter, κ. Tasks $z \in [0, \kappa]$ are automated, while tasks $z \in (\kappa, 1)$ are performed by labor.

Due to the functional form in (8), factor demand does not depend on factor prices:

$$x^*(z) = \begin{cases} \frac{n}{1-\kappa} & \text{if } z \in (\kappa, 1] \\ \frac{k}{\kappa} & \text{if } z \in [0, \kappa] \end{cases} \tag{9}$$

Plugging $x^*(z)$ into the production function, we get

$$y = \exp\left(\int_0^\kappa \ln \eta(z) dz + \int_\kappa^1 \ln \gamma(z) dz \right) \left(\frac{k}{\kappa} \right)^\kappa \left(\frac{n}{1-\kappa} \right)^{1-\kappa} \tag{10}$$

Capital and labor are perfectly mobile across firms. The maximisation problem of a monopolistically competitive firm reads:

$$\max_{\{k,n\}} py - rk - wn$$

s.t. (10) and $y = p^{-\sigma}$

This yields the the first order conditions:

$$wn = (1-\kappa)\Big(1-\frac{1}{\sigma}\Big)py \tag{11}$$

$$rk = \kappa\Big(1-\frac{1}{\sigma}\Big)py. \tag{12}$$

Solving for k in (11) and (12):

$$k = \frac{\kappa}{1-\kappa}\frac{w}{r}n \tag{13}$$

Substituting (13) in the production function (10) and taking logs, we get

$$\ln y = \int_0^{\kappa} \ln \eta(z)dz + \int_{\kappa}^{1} \ln \gamma(z)dz + \ln n - \ln(1-\kappa) + \kappa \ln\left(\frac{w}{r}\right) \tag{14}$$

Taking the log of (11) and substituting (14) into it, we obtain an expression for labor:

$$\ln n = (\sigma - 1)\left[\int_0^{\kappa} \ln \eta(z)dz + \int_{\kappa}^{1} \ln \gamma(z)dz + \kappa \ln\left(\frac{w}{r}\right)\right]$$

$$+\ln(1-\kappa) + \ln\left[w^{-\sigma}\Big(1-\frac{1}{\sigma}\Big)^{\sigma}\right] \tag{15}$$

Differentiating (15) with respect to κ, we obtain an expression showing that the employment effect is composed by a productivity effect ($\frac{\partial \ln y}{\partial \kappa}$) and a displacement effect ($-\frac{1}{1-\kappa}$):

$$\frac{\partial \ln n}{\partial \kappa} = \frac{\sigma-1}{\sigma}\frac{\partial \ln y}{\partial \kappa} - \frac{1}{1-\kappa} \tag{16}$$

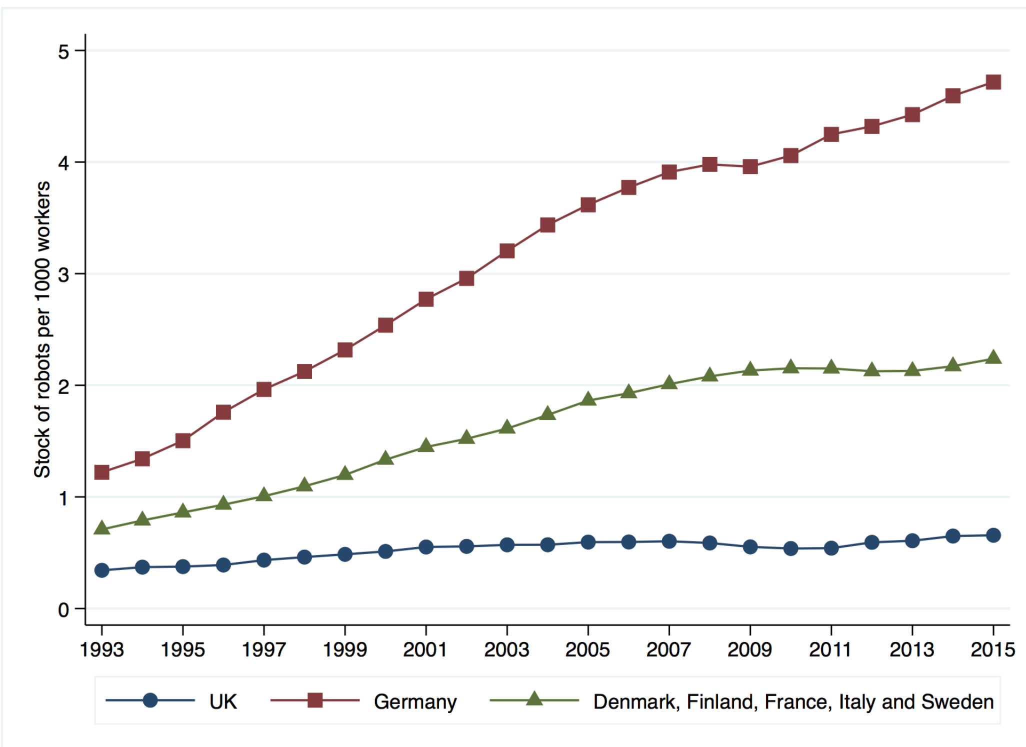
Using (14) and differentiating again (16) respect to κ, we obtain:

$$\frac{\partial^2 \ln n}{\partial\kappa\partial\kappa} = -(\sigma-1)\tilde{\gamma}'(\kappa) - \frac{1}{(1-\kappa)^2} < 0$$

Therefore, since automation exhibits diminishing productivity returns $\left(\frac{\partial^2 \ln y}{\partial\kappa\partial\kappa} < 0\right)$, robots are more likely to increase labor demand for initially low levels of automation.

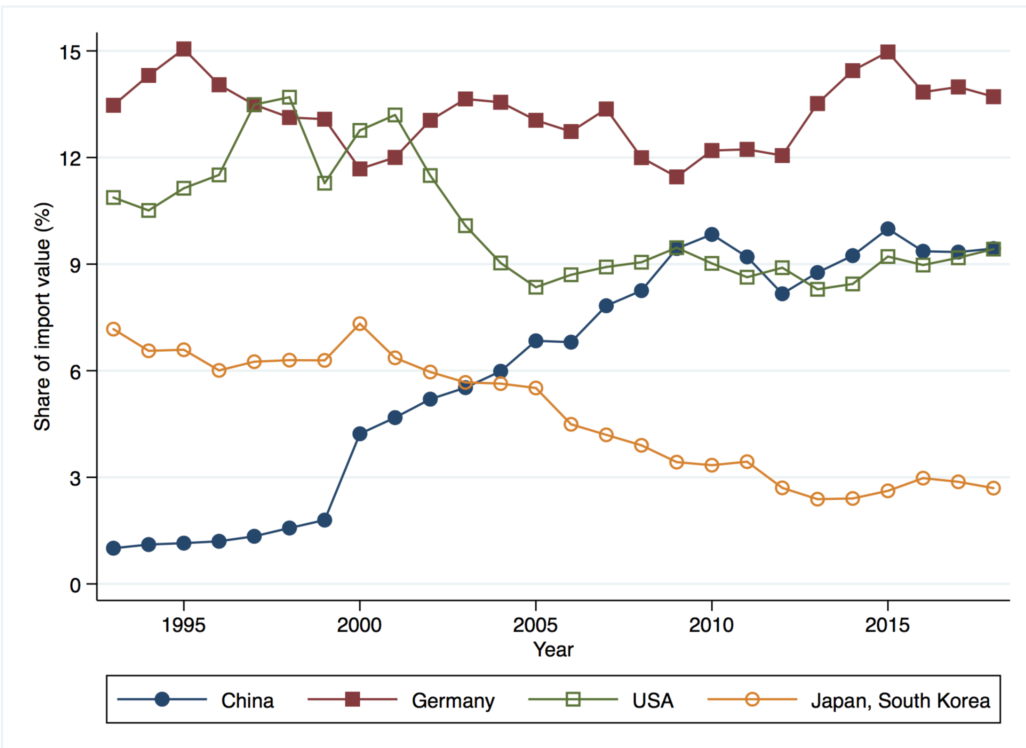
B Tables and Figures

Figure I: Industrial robots in the UK and Europe, 1993-2015.



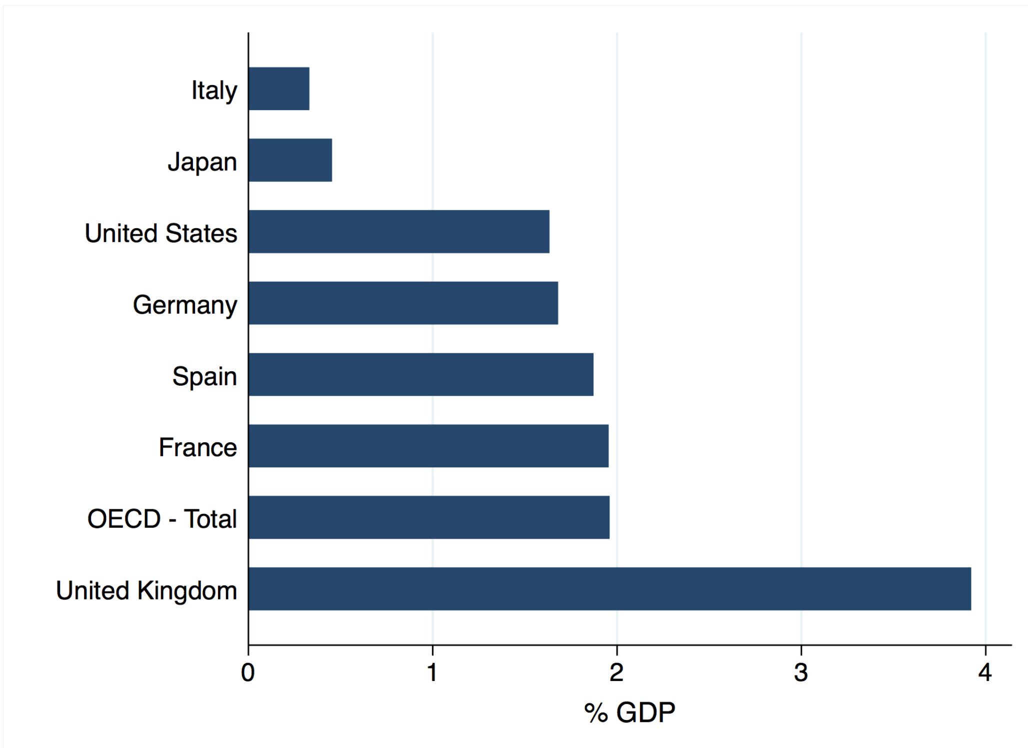
Sources: IFR and EUKLEMS.

Figure II: Total UK imports, 1993-2018.



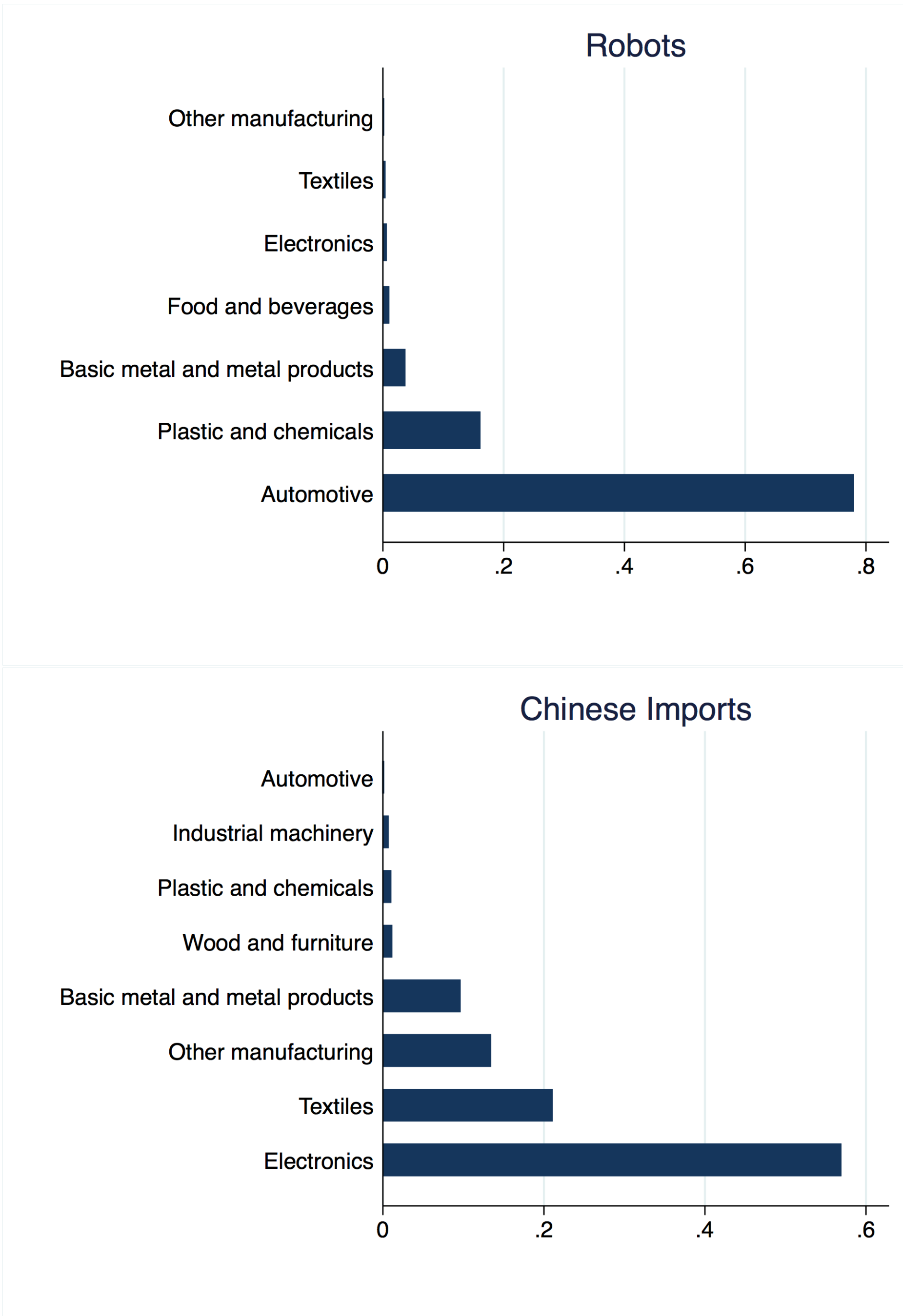
Source: UN Comtrade.

Figure III: FDI inward and outward flows (average 2005-2006)



Notes: This figure shows the average of inward and outward FDI flows over GDP for the years 2005-2006; Source: OECD.

Figure IV: Rotemberg weights.



Notes: This figure plots the positive Rotemberg weights by industry for robots and imports from China.

Table I: Identification test for industries with the largest Rotemberg weights.

	(1) Chemicals plastics	(2) Automotive	(3) Exposure to robots	(4) Textiles	(5) Electronics	(6) Exposure to Chinese import
Share of foreign-born (change 91-07)	0.001	0.003	0.120	0.001**	-0.000	0.315
	(0.002)	(0.003)	(0.085)	(0.000)	(0.000)	(0.331)
Population	-0.006*	0.000	-0.211	0.004***	0.004***	-0.939
	(0.003)	(0.004)	(0.161)	(0.001)	(0.001)	(0.607)
Share of over-65 population	-0.125	-0.346*	-12.683*	-0.048**	0.012	-22.852
	(0.146)	(0.206)	(7.363)	(0.019)	(0.020)	(22.898)
Share male pop.	-0.208	-0.930	-20.353	-0.138*	0.095	83.033
	(0.588)	(0.701)	(25.312)	(0.081)	(0.076)	(79.307)
Share white pop.	1.781*	3.373**	165.296***	0.469**	-0.366	174.467
	(1.024)	(1.406)	(48.650)	(0.207)	(0.250)	(158.339)
Share asian pop.	1.746*	3.062**	156.457***	0.583***	-0.386	220.490
	(0.983)	(1.354)	(47.049)	(0.211)	(0.239)	(149.383)
Share black pop.	1.599	3.305**	155.472***	0.532***	-0.314	136.133
	(1.033)	(1.448)	(50.447)	(0.197)	(0.238)	(159.703)
Share foreign-born pop.	0.236*	0.510**	21.175***	-0.050*	0.066*	-19.611
	(0.133)	(0.201)	(6.838)	(0.028)	(0.039)	(21.850)
Share of qualified workers	-0.102	-0.183	-8.000*	-0.054***	-0.002	-26.961
	(0.074)	(0.119)	(4.365)	(0.014)	(0.015)	(16.478)
Emp. light manuf. share	-0.043***	-0.016*	-1.828***	0.005**	-0.005***	-13.943***
	(0.017)	(0.009)	(0.407)	(0.002)	(0.002)	(2.553)
Emp. constr. share	0.099	-0.146*	-3.184	0.004	-0.029**	-26.119
	(0.169)	(0.086)	(3.553)	(0.017)	(0.014)	(16.192)
Emp. manuf. share	-0.009	-0.135***	-4.588**	0.007*	0.004	17.071**
	(0.041)	(0.051)	(2.067)	(0.004)	(0.005)	(6.655)
Share of routine emp.	0.049	-0.002	4.654*	-0.044***	-0.001	8.048
	(0.067)	(0.075)	(2.566)	(0.012)	(0.013)	(13.054)
Emp. mining share	-0.087	-0.054	-2.214	-0.007	0.032**	-19.707
	(0.067)	(0.060)	(2.732)	(0.015)	(0.012)	(13.342)
Emp-pop ratio (change 84-91)	0.000	0.000	0.006	0.000	-0.000	0.024
	(0.000)	(0.000)	(0.008)	(0.000)	(0.000)	(0.045)
Observations	352	352	352	352	352	352
R-squared	0.309	0.359	0.547	0.876	0.930	0.495
Region FE	✓	✓	✓	✓	✓	✓

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports, focusing on the industries with the largest Rotemberg weights. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese import in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table II: The impact of robots and Chinese imports on the UK employment-to-population ratio: excluding industries with the largest Rotemberg weights.

	(1) Emp-pop ratio	(2) Emp-pop ratio
Exposure to robots (excluding automotive)	-1.167***	
	(0.410)	
Exposure to Chinese imports (excluding electronics)		-0.169**
		(0.072)
Observations	352	352
R-squared	0.432	0.423
Region FE	✓	✓
Full set of base-year covariates	✓	✓

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration (excluding automotive) in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese imports (excluding electronics) in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table III: Alternative time periods: 1993-2015.

	(1) Emp-pop ratio (1993-2015)	(2) Emp-pop ratio (1993-2015)	(3) Emp-pop ratio (1993-2015)
Exposure to robots (1993-2015)	-0.340***		-0.250**
	(0.094)		(0.098)
Exposure to Chinese import (1993-2015)		-0.108***	-0.099***
		(0.023)	(0.023)
Observations	352	352	352
R-squared	0.577	0.607	0.618
Region FE	✓	✓	✓
Full set of base-year covariates	✓	✓	✓

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese import in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table IV: The impact of ICT and capital deepening.

	(1) Emp-pop ratio	(2) Emp-pop ratio	(3) Emp-pop ratio
Expsure to robots (instrument)	-0.457**		-0.439**
	(0.216)		(0.219)
Expsure to Chinese imports (instrument)		-0.074	-0.066
		(0.054)	(0.055)
Capital deepening	1.178	1.476	-0.447
	(5.183)	(4.951)	(5.003)
ICT capital	9.985	9.191	11.027
	(10.574)	(10.429)	(10.383)
Observations	352	352	352
R-squared	0.444	0.440	0.446
Region FE	✓	✓	✓
Base-year covariates	✓	✓	✓

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese import in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table V: Focusing on manufacturing employment.

	(1) Emp-pop ratio (manuf.)	(2) Emp-pop ratio (manuf.)	(3) Emp-pop ratio (manuf.)
Expsure to robots (instrument)	-0.212***		-0.195**
	(0.071)		(0.075)
Expsure to Chinese imports (instrument)		-0.067**	-0.064**
		(0.027)	(0.027)
Capital deepening	6.665***	5.959***	5.105***
	(1.572)	(1.759)	(1.749)
ICT capital	-4.246	-4.061	-3.245
	(3.500)	(3.596)	(3.596)
Observations	352	352	352
R-squared	0.621	0.626	0.633
Region FE	✓	✓	✓
Full set of base-year covariates	✓	✓	✓

Notes: This table presents OLS estimates of the relationship between the manufacturing employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese import in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table VI: The impact of globalization-related shocks.

	(1) Emp-pop ratio	(2) Emp-pop ratio	(3) Emp-pop ratio
Expsure to robots (instrument)	-0.579		-0.903*
	(0.473)		(0.492)
Expsure to Chinese imports (instrument)		-0.128*	-0.169**
		(0.072)	(0.074)
Export to China	4.484	-1.659	5.201
	(4.698)	(3.306)	(4.644)
Total export except China	38.528*	28.780*	51.069**
	(20.755)	(16.770)	(20.029)
Total import except China	-51.056**	-40.742**	-62.706***
	(20.285)	(16.600)	(19.487)
FDI inflow	8.234	19.364**	18.820**
	(8.261)	(8.848)	(9.461)
Offshorability index	-0.642	-0.462	-0.463
	(0.604)	(0.601)	(0.603)
Observations	352	352	352
R-squared	0.453	0.455	0.461
Region FE	✓	✓	✓
Base-year covariates	✓	✓	✓

Notes: This table presents OLS estimates of the relationship between the employment-to-population ratio and exposure to robots and Chinese imports. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese import in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.

Table VII: The impact of Chinese imports on the 2016 EU referendum as in Colantone & Stanig (2018).

	(1) Share of Vote Leave
Exposure to Chinese import (1993-2015)	0.175***
	(0.067)
Observations	347
R-squared	0.413
Region FE	NUTS-1
Full set of base-year covariates	X

Notes: This table presents OLS estimates of the relationship between the share of votes in favor of Brexit and exposure to robots and Chinese imports over the years 1993 to 2015. Robot exposure is the average robot penetration in five European countries ahead the United Kingdom in terms of automation as in Acemoglu & Restrepo (2020). Chinese import exposure is the average penetration of Chinese imports in eight high-income countries as in Autor et al. (2015). Standard errors are clustered at the city-level. The coefficients with *** are significant at the 1% level, with ** are significant at the 5% level, and with * are significant at the 10% level.