An individual-level analysis of the impact of industrial robot exposure on labour market transitions in the UK 1999-2015

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Abstract

This paper presents an individual-level analysis using longitudinal data from the BHPS, focusing on the short term effects of industrial robot exposure on the probability of transitioning from employment to unemployment. Individual-level analysis allows to more accurately estimate heterogeneous effects of an increase in robot exposure on individuals of different occupations, and in this way, test the widely accepted routine-biased technological change hypothesis in the context of industrial robots. Results suggest that overall, between 1999-2015, industrial robots have had no significant effect on labour market outcomes. There is weak evidence of an adverse effect on low-skilled, routine occupations, although this finding is not robust. Thus, displacement of workers does not appear to occur in the short run. Future studies should therefore consider other mechanisms through which adverse labour outcomes may occur, such as wages, vacancy creation, and other labour market transitions, such as early retirement.

4,999 words excluding Abstract, References & Appendix, including footnotes and main tables.

I am grateful to the IFR for granting me data access on industrial robot operational stock for 5 countries. I would like to thank Wolfgang Dauth and Sergio Correira for advice concerning the application of high-dimensional fixed effects.

I. Introduction

The impact of technological advance on employment has long been subject of debate, the Luddite revolution in the 1800s exemplifying worker's beliefs of being permanently displaced by technology (Hobsbawm, 1952). In the 20th century, Keynes (1930) predicted, among others (Leontief, 1952; Woirol, 1996), a "new disease…namely, technological unemployment". Despite such claims, previous periods of technological change have generally been associated with transitory unemployment, outweighed in the long run by the creation of new industries, occupations and higher labour productivity, verifying what economists refer to as the lump of labour fallacy.

However, revolutionary applications of information and communication technologies in the late 20th century have renewed fears of mass technological unemployment (Ford, 2015). In particular, the increasingly skill and routine-biased nature of technological change (Haldane, 2015) is fuelling concerns not so much regarding the creation of new jobs but rather the ability of displaced workers to adapt skills in the "race against man and machine" (Brynjolfsson and McAfee, 2011).

Empirical research estimating the impact of one such technology, industrial robots, on employment remains relatively unexplored. Inconclusive results suggest industrial robot exposure may be having country-specific effects, motivating this study which focuses on the UK.

In this paper, I exploit new data on industrial robots in conjunction with longitudinal data to provide novel insights regarding the short-term impact of a change in industrial robot exposure on the probability of becoming unemployed, as well as testing the validity of the routine-biased technological change hypothesis in the context of industrial robots.

II. Literature Review

Katz and Murphy (1992) revived the debate about how technology affects labour market outcomes, using a canonical supply-demand model to illustrate the increase in wage inequality since the 1980s, attributable to the complementary nature of technology for high-skilled workers, in contrast to a substitution effect on low-skilled workers, labelled Skill-Biased Technological Change (SBTC). Autor, Levy and Murmane (2003) refined the SBTC hypothesis, arguing that the impact of technology depends on worker's occupational routine-task intensity. There is widespread evidence of Routine-Biased technological change (RBTC), a broad consensus emerging that technological change benefits those performing both high and low-skill cognitive, non-routine tasks whilst negatively affecting routine middle-class occupations (Goos and Manning, 2007; Autor et al. 2006; Michaels et al. 2014). Cross-country studies conclude that RBTC has positively affected total employment, implying a dominant compensation effect through labour demand spillovers (Gregory et al. 2016; Goos et al. 2014).

A limitation of previous studies concerns the measurement of technological change; studies broadly use a routine-task-intensity index to predict outcomes of those in routine-intense occupations to those in more complex-task occupations (Autor, Levy and Murmane, 2003). However, this measure assumes workers more susceptible to automation are actually automated, failing to account for the employer's decisions to actually invest in automation. Indeed, evidence suggests that middle-skill routine occupations have been automated to a much greater extent than routineness indexes predict, whilst the opposite holds true for low-skilled workers, the reason being that low-paying routine jobs are less profitable to automate (Corlett and Gardiner, 2015; Feng and Graetz, 2015).Various studies seek to address this by using specific measures capturing the actual impact of technological investments on labour market outcomes. Michaels et al. (2014) find that industries with faster ICT capital growth shifted demand from middle to high-educated workers, with no effect on low-educated workers. Akerman et al. (2013) draw similar conclusions by analysing industry-level variation in internet broadband adoption. Clearly, such measures focus on the *complementarity* of technology rather than its potential to *replace* labour permanently; however, general technological advance and labour-displacing industrial robots[1] may be having differential impacts. For instance, Acemoglu and Restrepo (2017) find adverse effects of increased robot intensity on US regional employment, yet find no such negative effect of ICT intensity. Likewise, they find no positive effect of increased robot exposure on high-skilled workers, questioning the extent to which specific types of technology support the RBTC hypothesis.

Graetz and Michaels (2015) are among the first to empirically test the economic impact of robots, exploiting industry-level data from 17 countries. They find industry-country pairs experiencing greater increases in robot density from 1993-2007 experienced larger gains in labour productivity. Moreover, they find no significant effect of robot densification on aggregate hours worked, but after controlling for skill levels, find evidence of reduced hours worked by low-skilled workers.

Exploiting variation in robot exposure across 422 US commuting-zones, Acemoglu and Restrepo (2017) evaluate ambiguous effects of automation on employment and earnings. One effect, the displacement effect, occurs due to the direct substitution of workers holding output and prices constant, whilst a counteractive productivity effect results from reduced costs, increasing labour and product demand in a given industry. Furthermore, displaced workers may be absorbed by other industries, specialising in new tasks, referred to as spillover effect. Data from 1990-2007 indicate a significantly negative impact of robot usage on commuting-zone employment-to-population ratios, although the effect weakens after allowing for spillover effects through inter-commuting-zone trade. Findings also indicate reduced earnings across all skill groups, contradicting the RBTC hypothesis.

However, aforementioned studies are broadly limited to macro-level, general equilibrium outcomes exploiting industry or firm-level data, with few individual-level analyses. Although past studies contribute important insights concerning spillover effects across industries, regions or firms, they fail to offer deeper insights regarding

[1] The International Federation of Robotics (IFR) defines industrial robots as "an automatically controlled, reprogrammable, multipurpose manipulator programmable in three or more axes, which may be either fixed in place or mobile for use in industrial automation applications" (IFR, 2017).

heterogeneous impacts of automation across workers of different occupations, particularly in the short-term, partial equilibrium setting, which my research seeks to address.

Related to my research is the work of Dauth et al. (2016), who supplement German local labour market analysis with a novel longitudinal worker-level analysis. At the local labour market level, they find no adverse impact of robots on employment, concluding that automation induces *compositional* changes in aggregate employment, with one industrial robot leading to the loss of two low-skill manufacturing jobs, whilst creating new high-skill service jobs. This contrasts US estimates of one robot displacing 3-6 workers in aggregate.

At the individual level, the authors explain mechanisms through which automation affects employment and earning trajectories of different workers, as previously explored in the context of globalisation (Autor et al. 2013, 2015; Pessoa, 2014). They find that workers in more robot-exposed industries have a higher probability of remaining employed with their initial employer, but performing different tasks, inferring job stability and re-skilling of incumbent workers. However, this comes at the cost of lower wages for middle and low-skilled workers, attributable to labour institutions; German trade unions traditionally negotiate stable employment and lower wages in response to labour demand shocks, as opposed to more flexible US labour markets. However, as aforementioned, all skill groups experienced lower wages also in the US; perhaps robots are being applied differently in the US or German workers are more occupationally mobile, which could explain negative effects on *both* employment and earnings in the US.

The identification strategy employed by Dauth et al. (2016) involves regressing cumulative days worked from 1990-2015, based on the worker's base-year industry of employment, using a sample of manufacturing workers with strong labour market attachment. Consequently, results can be interpreted as long-run 20-year effects of increased robot exposure. However, this methodology is somewhat unsatisfactory as it fails to account for possible transitions between industries as a result of reskilling and adjustment to displacement, meaning robot exposure attributed to a worker may not represent their actual exposure and potentially conceal short-term displacement effects.

For this reason, I focus on the change in robot exposure in a given period and its contemporaneous impact on a worker's probability of transitioning to unemployment, more directly identifying short-run displacement effects.

This study tests the following hypotheses:

Hypothesis 1 (Displacement): Workers subject to a greater increase in robot exposure are more likely to become unemployed.

Hypothesis 2 (RBTC): Workers in middle and low-skill routine occupations are more likely to become unemployed following an increase in robot exposure, compared to workers in high-skill non-routine occupations.

III. Data

Data for my analysis comes from the British Household Panel Survey[2], which follows 5,500 households recruited in 1991. Approximately 10,000 individuals are re-interviewed each year until 2016 on a range of issues including labour force activity, wealth, and well-being.

To construct the dependant variable, the probability of transitioning from employment to unemployment, I limit the sample to individuals aged 16 to 65 who are employed in period $t-1$ and either employed or unemployed in period t. Similar to Donoso et al. (2015), I exclude self-employed workers due to difficulty in determining the real cause of unemployment, potentially confounding inference concerning displacement effects. Although ideally analysis would span from the early 1990s when robot exposure became pervasive and thus represented an exogenous shock (Acemoglu and Restrepo, 2017; Dauth et al. 2016), IFR data availability restricts analysis to the period 1999-2015. In addition, observations in 2009 are excluded, as this was the year of transition from BHPS to Understanding Society, during which original BHPS members were not interviewed. Retaining only those observations for which there are non-missing values for all key control variables, the final sample consists of 9,327 individuals, collectively recording 65,606 transitions from employment to either employment or unemployment.

The dataset also includes key individual and job characteristics, of which Summary statistics are displayed in Table 1. Importantly, the BHPS records the worker's SIC (Standard Industry Classification), which I merge with data from the IFR measuring UK yearly operational stock of industrial robots for 17 industries (listed in Table A.1), coded at the ISIC Rev 4 level. Using EUKLEMS data on employment across industries (at the NACE Rev 2 level), I construct my variable of interest, the change in robot exposure, namely the change in the number of robots per thousand workers in industry j between period t and $t-1$:

$$\Delta robot\_exposure_{jt} = \frac{no. of\ robots_{j,t}}{employment_{j,t}} - \frac{no. of\ robots_{j,t-1}}{employment_{j,t-1}}$$

I use industry-level EUKLEMS data measuring ICT capital investments and UN COMTRADE data on imports from China to the UK for each industry to account for potential confounding effects of ICT and globalisation respectively on employment. All variables are described in Table A.4.

The unconditional probability of transitioning from employment to unemployment (Table A.2) varies across skill level, with low-skilled workers as well as workers in plant operative and routine-service occupations more likely to transition into unemployment (see Table A.3 for detailed list of occupational groups).

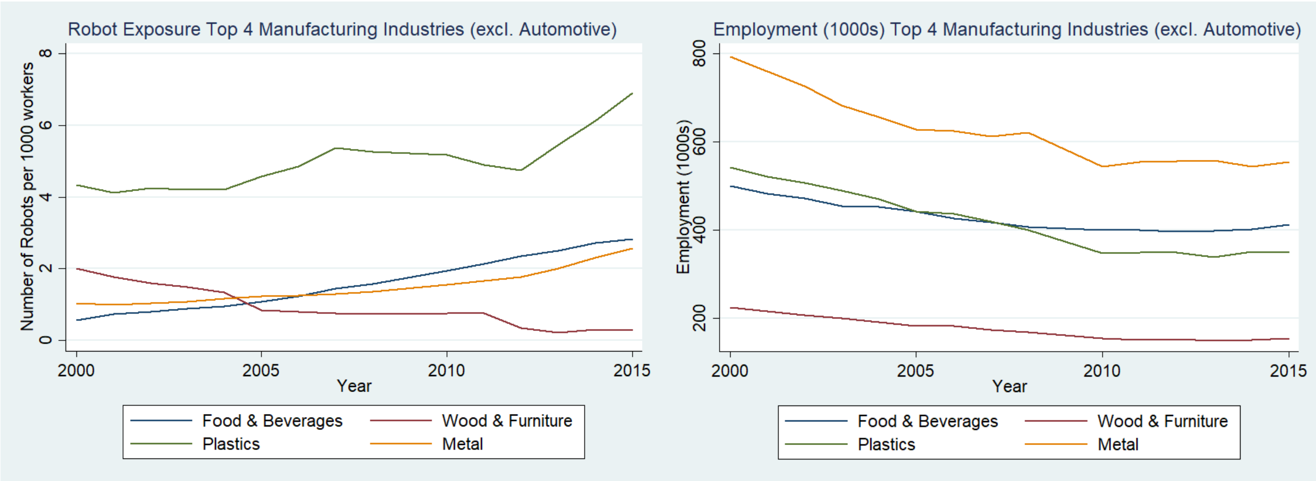
Figure 1 shows trends in robot exposure and employment for the top 5 manufacturing industries[3]. Somewhat negative correlation supports the suggestion that workers in more robot-exposed industries experience a higher probability of becoming unemployed (Hypothesis 1), although empirical analysis is needed to verify this.

[2] BHPS was replaced by Understanding Society in 2008, with similar survey questions.
[3] Excluding the automotive industry which has a much higher robot exposure above 65 robots per 1000 workers.

Table 1. Summary Statistics

Observations	**65,606**	**(9,327 individuals)**		
Variable	**Mean**	**S.D.**	**Min**	**Max**
Probability of becoming unemployed	0.017	0.129	0	1
Change in Robot Exposure	0.030	3.102	-65.389	65.390
Control Variables				
Gender	0.485	0.500	0	1
White	0.974	0.159	0	1
Age				
16-25	0.084	0.277	0	1
25-44	0.527	0.499	0	1
45-65	0.389	0.487	0	1
Married	0.588	0.492	0	1
Skill				
High	0.326	0.469	0	1
Medium	0.507	0.500	0	1
Low	0.166	0.372	0	1
Occupation				
Managerial & Professional	0.425	0.494	0	1
Clerical	0.159	0.366	0	1
Non-routine Services	0.267	0.442	0	1
Plant Operatives	0.101	0.302	0	1
Routine Services	0.048	0.214	0	1
Job size				
<25	0.326	0.469	0	1
25-200	0.362	0.481	0	1
>200	0.312	0.463	0	1
Broad industry[4]				
Primary	0.023	0.149	0	1
Manufacturing	0.143	0.350	0	1
Services	0.834	0.372	0	1
Change in Capital Exposure	0.010	0.073	-0.604	0.645
Change in Import Exposure	0.014	0.073	-0.966	0.960

Figure 1. Robot exposure and Employment trends



[4] See Table A.1.

IV. Methodology

To identify short-term displacement or productivity effects of automation, I base my benchmark analysis on the following econometric specification:

$$U_{ijt} = \beta \Delta robot\_exp_{jt} + \alpha_{ijt}\boldsymbol{X}'_{ijt} + \alpha_{wjt}\boldsymbol{X}'_{wjt} + \alpha_r + \alpha_{jt} + \varepsilon_{ijt} \qquad (1)$$

Where $U_{ijt} \begin{cases} = 1 & \text{if an individual transitions from employment in t-1 to unemployment in period t} \\ = 0 & \text{if an individual remains employed in both periods} \end{cases}$

The vectors $\boldsymbol{X}'_{ijt}$ and $\boldsymbol{X}'_{wjt}$ include individual and firm-level controls respectively.

Due to the binary nature of the dependent variable, I estimate a Linear Probability Model (LPM), often preferred to complex non-linear specifications due to simple inference and consistent, unbiased estimates under Gauss-Markov assumptions[5].

Controlling for unobserved heterogeneity across both industries and regions underpins the identification strategy, otherwise causing omitted variable bias in OLS estimates. It is likely there are time-invariant regional characteristics, such as cultural and local heterogeneity, necessitating the inclusion of region fixed effects. Similarly, time-varying employment trends and industry-specific demand shocks require industry-year fixed effects. However, since robot exposure is measured at the industry-year level, the change in robot exposure in a given industry and year is uniform for individuals who do not change the industry of employment in their transition, affecting an overriding proportion of the sample. This causes near perfect multicollinearity between the change in robot exposure and industry-year dummies[6]. Estimates based on such weak within-industry-year variation would be prone to severe bias and underestimation of standard errors.

One solution involves including year and industry fixed effects separately. However, this assumes a single time trend for all industries, ignoring time-varying, industry-specific shocks. To circumvent this issue, I draw inspiration from comparable studies by creating broad industry dummies (Dauth et al. 2016), grouping industries subject to similar trends and shocks (see Table A.1.), thereby avoiding multicollinearity. Moreover, it is probable that error terms for different individuals are correlated within industries in each year. Assuming shocks are uncorrelated between years for the same broad industry, standard errors are clustered at the broad-industry-year level.

I then enhance equation (1) to exploit the longitudinal nature of the dataset and estimate more accurately the impact of automation on individual labour market transitions by controlling for unobserved time-invariant individual heterogeneity, such as productivity or ability. Although there is sufficient within-individual variation for the change in robot exposure, the same does not hold for control variables, inhibiting inference from their fixed effects estimates[7]. Similarly, it is likely that the assumption that unobservable individual productivity is uncorrelated with the change in robot exposure (and other independent variables) over time, is violated, since robots may affect an individual's productivity over time, (Ross, 2015) meaning omitted variable bias may persist.

Subsequently, I test the RBTC hypothesis, altering the specification to include interactions with occupational status and stratifying equation (1) by occupational status to analyse how the coefficient on robot exposure changes across occupations.

[5] Inherent heteroscedasticity in the error term requires robust standard errors. I control more strictly for serial correlation by clustering standard errors at the industry-year level.
[6] I am grateful to Wolfgang Dauth and Sergio Correia for advice concerning fixed effects and the implementation of multi-dimensional fixed effects (Stata command 'reghdfe').
[7] This is particularly relevant for SOC (Table A.5.) which underpins RBTC analysis.

V. Results

Results, reported in Table 2, show that a change in robot exposure has no significant impact on the probability of becoming unemployed, in the absence of individual controls and fixed effects (Specification (1)). The coefficient remains insignificant after controlling for observable individual and firm-level characteristics, as well as accounting for region and broad-industry-year fixed effects (Specification (2)). Control variables have coefficients coherent with empirical findings; for the UK, there is evidence that male, white, married, older, more educated individuals are less likely to transition from employment to unemployment with respect to their base groups (Gomez, 2010). More relevant for my research question, we observe that workers in clerical, non-routine-service, plant operative and routine-service occupations are significantly more likely to become unemployed compared to workers in managerial occupations. Routine plant operative occupations are most likely to become unemployed, and routine low-skilled services to a slightly lesser extent. Whilst this somewhat corresponds to the RBTC hypothesis, the coefficients fail to capture the widely cited “hollowing out” of middle-class clerical occupations (Corlett and Gardiner, 2015).

Specification (3) controls for unobserved time-invariant individual heterogeneity. Individual-related variables that do not change during the sample period, namely gender and race, are absorbed. Similarly, region fixed effects are excluded due to minimal movement of individuals across regions. The coefficient on the change in robot exposure remains insignificant, but becomes more negative, implying positive omitted variable bias due to a positive correlation between unobserved individual heterogeneity and the change in robot exposure. However, as aforementioned, it is likely, in this context, that unobserved individual productivity is time-varying and strips out much within-variation. Thus, there is a trade-off between reducing omitted variable bias and having sufficient within-variation for meaningful inference. Since this study aims to explore RBTC effects (see below), individual fixed effects are not included in further specifications.

Specification (4) controls for other labour market trends occurring since the 1990s, namely computerisation and Chinese import exposure. Since import data is only available for manufactured goods, the sample only includes observations in manufacturing industries. Adding import and capital exposure does not change the coefficient of interest, implying orthogonality of trends. The insignificant coefficient on import exposure contrasts findings that rising Chinese import exposure has worsened UK labour market outcomes (Pessoa, 2014). However, measurement error is likely as SICs in the BHPS are aggregated at a higher level than UN COMTRADE data, failing to capture more import-specific effects.

Overall, results point to an insignificant impact of automation on labour market outcomes, suggesting that technological displacement is a misconception, with an increase in the 1 industrial robot per 1000 workers (representing a sizeable increase given an average level of 0.7 industrial robots per 1000 workers) having no significant impact on the probability of becoming unemployed. No evidence of either displacement or productivity effects contradicts US findings of adverse effects on employment (Acemoglu and Restrepo, 2017), yet is consistent with findings in Germany of a neutral overall impact of automation (Dauth et al. 2016).

The latter findings are justified by compositional changes, as low-skilled, routine manufacturing workers suffer from automation compared to high-skilled service workers. Thus, insignificant results may conceal differential impacts of increased robot exposure among workers in different occupations. To explore whether the RBTC hypothesis holds in the UK context, the baseline specification (equation (1)) is enhanced by adding 4 interaction dummies between the change robot exposure and occupational classification, as well as stratifying by occupation. Results are displayed in Table 3, (see Table A.6. for other variables).

Table 2. Main Results

Dependant Variable: Probability of becoming unemployed	(1)	(2)	(3)	(4)
Δ Robot Exposure	0.00000	-0.00006	-0.00012	-0.00020
	(0.00014)	(0.00015)	(0.00017)	(0.00023)
Male (cf Female)		0.00517***		
		(0.00166)		
White (cf Non-white)		-0.00740*		
		(0.00434)		
Age (cf 16-25)				
25-44		-0.01708***	-0.00824**	-0.03954***
		(0.00267)	(0.00394)	(0.01062)
45-65		-0.01745***	-0.00454	-0.03554***
		(0.00274)	(0.00519)	(0.01046)
Married (cf Single)		-0.01176***	-0.00344	-0.02095***
		(0.00116)	(0.00268)	(0.00436)
Skill Level (cf High-skilled)				
Medium-skilled		0.00229**	0.01190	0.00695**
		(0.00109)	(0.00866)	(0.00324)
Low-skilled		0.00809***	0.00540	0.02066***
		(0.00199)	(0.00796)	(0.00498)
SOC (cf Managerial & Professional)				
Clerical		0.00384**	0.00092	-0.00753
		(0.00167)	(0.00256)	(0.00615)
Non-routine Services		0.00673***	0.00135	-0.00329
		(0.00135)	(0.00258)	(0.00450)
Plant Operatives		0.01269***	0.00298	-0.00562
		(0.00228)	(0.00506)	(0.00468)
Routine Services		0.00967***	-0.00388	0.03305*
		(0.00258)	(0.00432)	(0.01664)
Firm size (cf <25 employees)				
25-200		-0.00510***	-0.00598**	-0.00975**
		(0.00120)	(0.00230)	(0.00472)
>200		-0.00898***	-0.00832***	-0.01876***
		(0.00147)	(0.00261)	(0.00551)
Change in Import Exposure				-0.01742
				(0.01269)
Change in Capital Exposure				-0.01522
				(0.04015)
Constant	0.01706***			
	(0.00099)			
Broad Industry-Year FEs	Yes	Yes	Yes	Yes
Region FEs	No	Yes	No	Yes
Individual FEs	No	No	Yes	No
Observations	65,606	65,606	65,606	8,032
R-squared	0.00000	0.01042	0.25620	0.0221

Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

Table 3. RBTC Hypothesis

Dependant Variable: Probability of becoming unemployed	*Interaction*	*Managerial*	*Clerical*	*N-R services*	*Plant operatives*	*Routine services*
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Robot Exposure	-0.00035	-0.00031	0.00030	-0.00000	0.00002	0.00045
	(0.00032)	(0.00032)	(0.00021)	(0.00013)	(0.00020)	(0.00046)
SOC*Δ Robot Exposure						
(cf Managerial & Professional)						
Clerical*Δ Robot Exposure	0.00032					
	(0.00036)					
Non-routine Services*Δ Robot Exposure	0.00034					
	(0.00027)					
Plant operatives*Δ Robot Exposure	0.00044					
	(0.00035)					
Routine-services*Δ Robot Exposure	0.00096*					
	(0.00054)					
Observations	65,606	27,861	10,455	17,488	6,642	3,156
R-squared	0.01044	0.00601	0.01221	0.01245	0.02978	0.03665

All specifications include industry-year and region fixed effects. Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

The weakly significant coefficient on the interaction for routine-services implies an increase in robot exposure leads to a higher probability of becoming unemployed for workers in routine-service occupations than workers in managerial occupations (the base group). This may appear surprising as this category includes workers in hospitality, which do not seem automatable. Yet, the same category also includes shelf fillers and postal workers, highly prone to automation (Nedelkoska and Quintini, 2018). This also attests to claims that it is low-skilled routine occupations, rather than middle-skilled routine occupations which are being adversely impacted by technology, implying a different nature of RBTC compared to ICT (Graetz and Michaels, 2015). This finding would likewise support emerging research that RBTC, which is “hollowing out” middle class occupations in its more traditional sense, is not attributable to automation, but rather to other factors such as globalisation or supply-side factors such as increased female labour market participation or upskilling of the workforce (Corlett and Gardiner, 2015). However, above findings are not robust to stratification across occupations (Specifications (2)-(6)), placing doubt on the above claims.

VI. Extension

Heterogeneous effects of automation evidenced by Dauth et al. (2016) have a more nuanced intuition in that incumbent manufacturing workers have an increased probability of staying employed with the same employer in response to automation, the adverse effect feeding through to new-entry manufacturing workers, who are less likely to find a job as less vacancies are created. To see whether the same holds true for UK data, I conduct a similar analysis on the probability of being employed in the same industry[8].

From Table A.7., there is no evidence that workers are more likely to remain employed in the same industry following an increase in exposure to industrial robots. Thus, it appears industrial robots are not impacting labour market outcomes more generally, although a more detailed analysis of entry into the labour market would be needed to verify this (Dauth et al. 2016). Similarly, whilst employment transitions may not be affected, it could be that workers prone to robot exposure are losing bargaining power, or leaving the labour force altogether, opting for early retirement (Burlon & Vilalta-Bufí, 2016) or considering themselves unable to retrain (Krause & Sawhill, 2017) which may not be captured by the dependant variable used in this study.

VII. Robustness Checks

I now conduct a battery of robustness checks to verify the above findings. Firstly, robot exposure is significantly higher in the automotive industry relative to other industries, which could be driving results. Estimating the baseline specification only on observations in the automotive industry, we observe that an increase in robot exposure significantly reduces the probability of becoming unemployed (Column (1), Table A.8.), whilst the coefficient of interest remains insignificant for the rest of the sample (Column (2)). Thus, the automotive industry, subject to a much higher increase in robot exposure compared to other industries, may be experiencing unique productivity effects. Interacting the change in robot exposure by occupation, we find no evidence of RBTC in the automotive industry (Column (3)), but now observe a weakly positive interaction term for both plant operative and routine-service occupations for all other industries (Column (4)). Removal of the potential outlier industry shows that the overall insignificant coefficient on the change in robot exposure conceals a weakly adverse effect on routine, low-skilled occupations, with respect to more complex, high-skilled occupations, somewhat more consistent with recent literature (Graetz and Micheals, 2015; Dauth et al. 2016), although significance remains weak.

One explanation for this may be the aptness of the measure of robot exposure, which only captures the change in robot exposure in one period, ignoring cumulative aspects of industrial robot investment (Dauth et al. 2016)[9]. Although the aim of this study is indeed to analyse partial equilibrium outcomes, which are more likely to be negative due to labour market frictions, it is possible that a one year change is too short a time period to grasp any meaningful short-term effects, as the mechanism through which automation displaces workers may take longer than 1 year. Moreover, assuming the measure were sufficient, it is possible that robot investments 1 or 2 years ago affect labour market outcomes today, rather than contemporaneous investments. Replacing the change in robot exposure with its 1 and 2 year lags respectively does not affect the significance of the coefficient of interest (See Table A.9.), meaning findings are robust to changes in robot exposure up to 2 years ago.

Finally, the 2008 financial crisis may be confounding results. Indeed, many analyses to date have stopped at 2008 (Acemoglu and Restrepo, 2017, Autor et al. 2014). However, splitting the sample shows that the insignificance of the coefficient of interest is robust to both the pre and post crisis period (See Table A.9.).

[8] Data limitations do not permit the determination of whether a worker remains with the same employer. Thus, analysis assumes workers staying in the same industry remain with the same employer, somewhat questionable.

[9] A comparable long-term analysis is not feasible due to the unbalanced panel and the small number of observations recorded over the whole period, inducing selection bias.

VIII. Limitations

Despite results indicating insignificant effects of automation on labour market transitions, several limitations affect the ability to make policy recommendations based on the results presented.

Firstly, the LPM is prone to severe limitations. Although fitted values of the dependent variable are broadly bounded between 0 and 1[10], endorsing the application of the LPM, the extremely small unconditional probability of becoming unemployed (0.017), means possibly large deviations from the true coefficient compared to a non-linear Logit specification, which bounds fitted values by assuming a logistic distribution of the error term. Running a logit and conditional logit specification (including individual fixed effects) respectively indicates an insignificant coefficient on the change in robot exposure (Table A.10.), with control variable coefficients broadly corresponding to OLS estimates, implying robustness across specifications.

Moreover, the change in robot exposure, measured at the industry-level, is prone to measurement error as we assume all workers in the same industry are exposed homogenously. Results would be more precise if robot exposure were recorded at the individual level, which increasing availability of comprehensive employer-employee surveys may make feasible in the future.

Furthermore, it is likely that results still suffer from omitted variable bias, as the BHPS lacks a measure of job tenure and contract type. This may be an important omission as short-term contracts may mean transitions to unemployment occur due to contracts ending rather than displacement (Donoso et al. 2015). However, Donoso et al's (2015) analysis concerns the Spanish labour market, where short-term contracts are much more pervasive. This form of omitted variable bias should of less concern in the UK context.

IX. Endogeneity

A source of endogeneity bias may arise from UK-specific labour market shocks affecting both employment transitions and the change in robot intensity. To address this, I adopt an instrumental variable strategy replicating other studies (Dauth et al. 2016; Autor et al. 2015). In this case, I instrument UK robot exposure with that of Italy[11]. This represents an exogenous technological change under the assumption that the UK labour market shocks are unrelated to those of Italy; arguably more plausible than Dauth et al's (2016) assumption that German labour markets shocks are unrelated to those of EU neighbours, whose labour markets are more integrated. First-stage regression results (Column (1), Table A.11.) show that Italian robot exposure is positively related to UK robot exposure, a high F-statistic indicating relevance[12]. Reduced-form estimates are displayed in Column (2) of Table A.11. Although instrument exogeneity cannot be tested due to just-identification, the fact that results are not altered, with insignificance persisting, suggests that endogeneity is not causing significant bias in the coefficient, thereby reinforcing the finding that displacement effects of industrial robots do not hold true empirically in the short-run.

[10] See Figure A.2.

[11] Instrumenting UK robot exposure with US robot exposure is not feasible as US data is only broken down by industry after 2004 and Japanese data also uses incomparable industry classifications up to 2004 (IFR).

[12] F-stat= 3300.61 is of a comparable size to that found by Dauth et al (2016) in their study.

X. Conclusion

This study proposes that the largely perceived negative relationship between robot exposure and employment does not hold true empirically in the short-run, robust to a number of specifications. However, some evidence is found of more adverse effects of automation on low-skilled routine occupations, somewhat suggesting that industrial robots are impacting labour market outcomes in a different way than technological progress to date, which has mainly been affecting middle-class clerical occupations (Graetz and Michaels, 2015; Acemoglu and Autor 2011; Goos and Manning 2007). Yet, this finding is only significant at the 10% level. Thus, findings contrast those of other countries focusing on long-term impacts (Acemoglu and Restrepo, 2017; Dauth et al. 2016), indicating that displacement or other labour market effects may only become apparent in the long run. Similarly, it may be that industrial robots are having unique effects across countries, meaning institutional factors such as wage-bargaining structures and labour market flexibility determine how automation affects workers.

Any substantial claims concerning automation can only be made in conjunction with further studies on the effect of automation on wage-bargaining power of individuals, as well as perhaps more nuanced mechanisms through which automation may affect jobs, for instance through retaining and retraining workers or displacing them. Likewise, this study focusing on the short-term impact of automation over the period 1999-2015, by no means invalidates potentially harmful (or beneficial) long-term effects or claims that future developments in robotics may replace workers, particularly in light of recent announcements encouraging higher investments in automation and susceptibility to automation in a growing number of occupations (Frey & Osbourne, 2017).

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Appendix

Table A.1. Summary Statistics for industries and regions

Observations	**65,606**	**(9327 individuals)**		
	Mean	**S.D.**	**Min**	**Max**
Control Variables (used for Fixed Effects)				
Industries				
Primary				
1. Agriculture, forestry & fishing	0.007	0.083	0	1
2. Mining & quarrying	0.006	0.078	0	1
3. Glass, ceramics, stone & minerals	0.005	0.069	0	1
4. Textiles	0.006	0.076	0	1
Manufacturing				
5. Wood & furniture	0.005	0.069	0	1
6. Paper	0.015	0.122	0	1
7. Plastic & chemical products	0.024	0.154	0	1
8. Food & beverages	0.022	0.148	0	1
9. Metal	0.031	0.173	0	1
10. Electrical products	0.017	0.130	0	1
11. Automotive	0.009	0.092	0	1
12. Other vehicles	0.008	0.090	0	1
13. All other manufacturing	0.011	0.104	0	1
Services				
14. Electricity, gas & water supply	0.015	0/120	0	1
15. Construction	0.045	0.208	0	1
16. Education & R&D	0.116	0.320	0	1
17. All other services	0.658	0.474	0	1
Regions				
North East	0.039	0.192	0	1
North West	0.078	0.267	0	1
Yorkshire & Humberside	0.063	0.243	0	1
East Midlands	0.062	0.241	0	1
West Midlands	0.054	0.226	0	1
East Anglia	0.039	0.193	0	1
London	0.051	0.219	0	1
South East	0.125	0.331	0	1
South West	0.063	0.244	0	1
Wales	0.176	0.381	0	1
Scotland	0.210	0.407	0	1
N. Ireland	0.040	0.199	0	1

Table A.2 – Unconditional Probability of becoming unemployed by Skill and Occupation

Year	All(%)	Skill(%) High	Skill(%) Med	Skill(%) Low	Occupation(%) Prof.	Occupation(%) Clerical	Occupation(%) N-R Services	Occupation(%) Plant Op.	Occupation(%) R Services
1999									
2000	**1.31**	0.61	1.28	2.31	0.45	1.94	1.89	2.16	0.46
2001	**1.31**	0.75	1.23	2.24	0.62	1.01	1.79	2.39	2.40
2002	**1.77**	0.73	1.93	2.91	0.79	1.57	2.44	3.85	1.96
2003	**1.60**	1.12	1.54	2.51	1.12	1.17	1.81	2.96	2.89
2004	**1.56**	1.16	1.66	1.89	0.98	1.32	1.94	2.83	2.08
2005	**2.08**	1.18	2.45	2.51	1.44	1.95	2.94	2.50	1.83
2006	**1.65**	0.84	1.86	2.47	0.72	2.28	2.53	2.47	1.46
2007	**1.33**	0.7	1.74	1.21	0.81	1.47	2.05	0.89	2.73
2008	**2.18**	1.73	2.13	3.27	1.73	1.56	2.47	3.88	3.89
2010	**2.46**	1.21	3.02	3.56	1.44	2.81	3.13	4.81	2.49
2011	**1.67**	1.23	1.74	2.59	0.98	1.10	2.34	3.01	3.65
2012	**2.45**	1.36	2.64	4.99	1.53	1.43	3.27	6.04	3.06
2013	**1.68**	1.25	1.88	2.37	1.38	2.08	0.87	3.53	3.55
2014	**0.91**	0.89	0.97	0.66	0.55	1.01	1.04	1.02	3.05
2015	**1.58**	1.05	1.88	2.44	1.05	0.53	2.62	2.61	2.48

Table A.3 – SOC Classifications

Managerial & Professional

Corporate managers and senior officials
Functional managers
Quality and customer care managers
Financial institution and office managers
Health and social services managers
Managers in agriculture
Managers and proprietors in hospitality
Managers and proprietors: other services
Science professionals
Health professionals
Teaching professionals
Research professionals
Legal professionals
Business and statistical professionals
Architects, town planners, surveyors
Public service professionals
IT service delivery occupations
Social welfare associate professionals
Artistic and literary occupations
Media associate professionals
Sports and fitness occupations
Transport associate professionals

Clerical

Administrative occupations: government
Administrative occupations: finance
Administrative occupations: records
Administrative occupations: communications
Administrative occupations: general
Secretarial and related occupations

Non-routine Services

Agricultural trades
Metal forming, welding & related trade
Vehicle trades
Electrical trades
Construction trades
Textiles and garments trades
Printing trades
Food preparation trades
Healthcare and related personal service
Animal care services
Leisure and travel service occupations
Hairdressers and related occupations
Personal services occupations
Sales related occupations
Customer service occupations

Plant Operative

Process operatives
Plant and machine operatives
Assemblers and routine operatives
Construction operatives
Transport drivers and operatives
Mobile machine drivers and operatives
Elementary agricultural occupations
Elementary process plant occupations

Routine Services

Elementary construction occupations
Elementary process plant occupations
Elementary goods storage occupations
Elementary administration occupations
Elementary personal services occupations
Elementary cleaning occupations
Elementary security occupations
Elementary sales occupations
Elementary sales occupations

Table A.4 – Variable Construction & Sources

Variable	Values	Definition	Source
emp_to_unemp	1 = transition to unemployment 0 = remain employed	Probability of transitioning from employment in period t-1 to unemployment in period t	BHPS
gender	0 = Female 1 = Male	Gender of individual	BHPS
white	0 = Non-white 1 = White	Race of individual: Non-white = Black, Asian, Chinese, Mixed, Other	BHPS
age_n	1 = 16-24 2 = 25-44 3 = 45-65	Age of individual at time of interview	BHPS
skill	1 = High-skilled 2 = Mid-skilled 3 = Low-skilled	Highest educational qualification: High-skilled = Degree, Other Higher Degree Mid-skilled = A Level etc, GSCE etc Low-skilled = Other qualification, No qualification	BHPS
soc_new	1 = Managerial & Professional 2 = Clerical 3 = Non-routine services 4 = Plant operatives 5 = Routine services	Occupational status of individual: Detailed breakdown in Table A.3.	BHPS
job_size	1 = <25 2 = 25-200 3 = >200	Number of employees in the workplace of the individual	BHPS
sic	1 – 17 industries (Table A.1)	Industry of current employment	BHPS
broad_sic	1 = Primary 2 = Manufacturing 3 = Services	Industry of current employment	BHPS
region	1 – 12 regions (Table A.1)	Region of residence of individual	BHPS
auto	0 = Non-automotive industry 1 = Automotive industry	Industry of current employment	BHPS
manuf	0 = Non-manufacturing industry 1 = Manufacturing industry	Industry of current employment	BHPS

Variable[13]	Values	Definition	Source/Comments
change_robot_exp	Continuous	Change in the number of robots per 1000 workers between period t and t-1	IFR: Annual operational stock of industrial robots by industrial branch - ISIC Rev 4) EUKLEMS: Number of people employed in 1000s by industrial branch - NACE Rev 2)
change_capital_exp	Continuous	Change in capital volume of computing and communications equipment per 1000 workers between period t and t-1	EUKLEMS: Real gross fixed capital formation volume (2010 prices) by industrial branch – NACE Rev 2) EUKLEMS: Number of people employed in 1000s by industrial branch - NACE Rev 2)
change_import_exp	Continuous	Change in trade value of Chinese imports per 1000 workers between period t and t-1	UNCOMTRADE: Trade value (US$) of Chinese imports to the UK by SITC Rev 4 commodity code EUKLEMS: Number of people employed in 1000s by industrial branch - NACE Rev 2)

[13] Change variables for individuals that become unemployed or have a missing value have an industry assigned to them as the industry of employment in period t-1.

Figure A.1. Distribution of fitted values of dependent variable

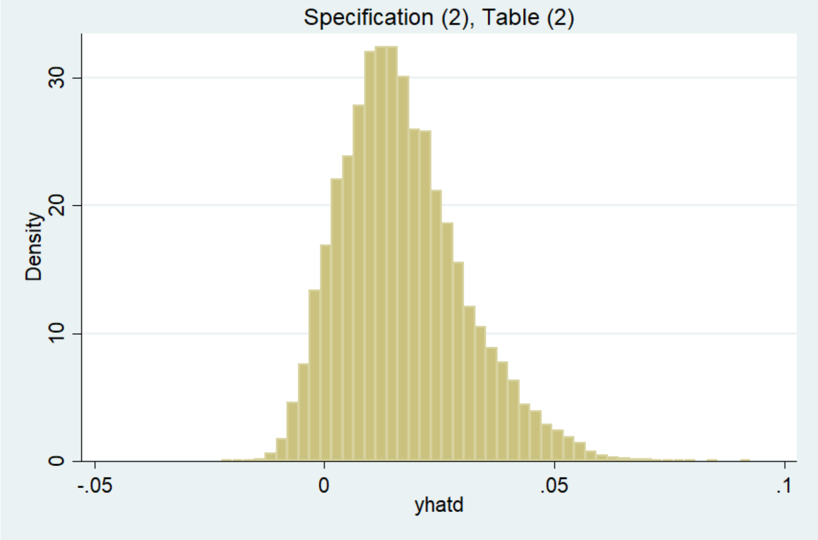

Table A.5. Variation in Key Variables

Variable		Mean	S.D.
Change in Robot Exposure	Overall	0.03	3.10
	Between		1.04
	Within		3.01
Gender	Overall	0.485	0.500
	Between		0.500
	Within		0
White	Overall	0.974	0.159
	Between		0.159
	Within		0
Age_n	Overall	2.305	0.616
	Between		0.611
	Within		0.282
Marital	Overall	0.588	0.492
	Between		0.461
	Within		0.207
Skill	Overall	1.840	0.684
	Between		0.681
	Within		0.117
Soc_new	Overall	2.189	1.222
	Between		1.095
	Within		0.603
Job_size	Overall	1.985	0.799
	Between		0.691
	Within		0.427
Region	Overall	7.622	3.333
	Between		3.305
	Within		0.441
SIC	Overall	15.144	3.789
	Between		3.308
	Within		1.871
No. of observations = 65606		No. of individuals = 9327	
Average no. of obs. per individual = 7.03			

Table A.6. RBTC Hypothesis (including control variables)

Dependent Variable: Probability of becoming unemployed	*Interaction*	*Prof.*	*Clerical*	*N-R Services*	*Plant Op.*	*Routine Services*
	(1)	(2)	(3)	(4)	(5)	(6)
Δ Robot Exposure	-0.00035	-0.00031	0.00030	-0.00000	0.00002	0.00045
	(0.00032)	(0.00032)	(0.00021)	(0.00013)	(0.00020)	(0.00046)
SOC*Δ Robot Exposure						
(cf Managerial & Professional)						
Clerical*Δ Robot Exposure	0.00032					
	(0.00036)					
Non-routine Services*Δ Robot Exposure	0.00034					
	(0.00027)					
Plant operatives*Δ Robot Exposure	0.00044					
	(0.00035)					
Routine services*Δ Robot Exposure	0.00096*					
	(0.00054)					
Gender	0.00517***	0.00265**	0.00756*	0.00561	0.00544	0.01537***
	(0.00166)	(0.00117)	(0.00421)	(0.00404)	(0.00676)	(0.00538)
White	-0.00742*	-0.01169*	0.00786	-0.01195	-0.01042	0.01340
	(0.00434)	(0.00653)	(0.00559)	(0.00836)	(0.01959)	(0.01142)
Age (cf 16-25)						
25-44	-0.01709***	0.00137	-0.02291***	-0.01244**	-0.05370***	-0.02208
	(0.00267)	(0.00285)	(0.00733)	(0.00503)	(0.01245)	(0.01785)
45-65	-0.01746***	0.00243	-0.02301***	-0.01067*	-0.05896***	-0.02667
	(0.00273)	(0.00318)	(0.00849)	(0.00564)	(0.01287)	(0.01632)
Married (cf Single)	-0.01176***	-0.00541***	-0.00778***	-0.01876***	-0.02175***	-0.01852***
	(0.00116)	(0.00102)	(0.00229)	(0.00229)	(0.00566)	(0.00546)
Skill Level (cf High-skilled)						
Medium-skilled	0.00229**	0.00353***	0.00142	0.00243	0.01114*	0.00151
	(0.00109)	(0.00129)	(0.00163)	(0.00183)	(0.00559)	(0.00719)
Low-skilled	0.00809***	0.00516*	0.00475	0.00671*	0.02328***	0.01541*
	(0.00199)	(0.00274)	(0.00485)	(0.00353)	(0.00603)	(0.00822)
SOC (cf Managerial & Professional)						
Clerical	0.00384**					
	(0.00167)					
Non-routine Services	0.00673***					
	(0.00135)					
Plant Operatives	0.01265***					
	(0.00228)					
Routine Services	0.00970***					
	(0.00257)					
Firm size (cf <25 employees)						
25-200	-0.00510***	-0.00089	-0.00057	-0.00907***	-0.01199*	-0.01454*
	(0.00120)	(0.00155)	(0.00258)	(0.00270)	(0.00598)	(0.00757)
>200	-0.00899***	-0.00398***	-0.00276	-0.01510***	-0.01667**	-0.02911***
	(0.00147)	(0.00148)	(0.00330)	(0.00331)	(0.00666)	(0.00775)
Observations	65,606	27,861	10,455	17,488	6,642	3,156
R-squared	0.01044	0.00601	0.01221	0.01245	0.02978	0.03665

All specifications include broad-industry-year and region fixed effects. Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

Table A.7. Extension: Other Labour Market Transitions

Dependent Variable:	*E→U*	*E→E_Diff*	*E→E_Same*
	(1)	(2)	(3)
Δ Robot Exposure	-0.00006	-0.00139	0.00144
	(0.00015)	(0.00309)	(0.00302)
Gender	0.00517***	0.02774***	-0.03291***
	(0.00166)	(0.00461)	(0.00486)
White	-0.00740*	-0.00009	0.00749
	(0.00434)	(0.00451)	(0.00676)
Age (cf 16-25)			
25-44	-0.01708***	-0.02884***	0.04591***
	(0.00267)	(0.00552)	(0.00591)
45-65	-0.01745***	-0.04718***	0.06464***
	(0.00274)	(0.00630)	(0.00658)
Married (cf Single)	-0.01176***	-0.00275	0.01451***
	(0.00116)	(0.00267)	(0.00314)
Skill Level (cf High-skilled)			
Medium-skilled	0.00229**	-0.00822**	0.00593*
	(0.00109)	(0.00326)	(0.00349)
Low-skilled	0.00809***	-0.00810**	0.00000
	(0.00199)	(0.00372)	(0.00338)
SOC (cf Managerial & Professional)			
Clerical	0.00384**	0.01391***	-0.01775***
	(0.00167)	(0.00495)	(0.00455)
Non-routine Services	0.00673***	0.01391***	-0.02064***
	(0.00135)	(0.00422)	(0.00431)
Plant Operatives	0.01269***	0.01159	-0.02428**
	(0.00228)	(0.00991)	(0.00969)
Routine Services	0.00967***	0.02403***	-0.03370***
	(0.00258)	(0.00739)	(0.00689)
Firm size (cf <25 employees)			
25-200	-0.00510***	-0.00348	0.00858**
	(0.00120)	(0.00340)	(0.00355)
>200	-0.00898***	-0.02318***	0.03216***
	(0.00147)	(0.00620)	(0.00659)
Observations	65,606	65,606	65,606
R-squared	0.01042	0.08139	0.07899

All specifications include broad-industry-year and region fixed effects. Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

Table A.8. Robustness Checks: Automotive Industry

Dependent Variable: Probability of becoming unemployed	*Auto Only*	*Excluding Auto*	*Auto Only*	*Excluding Auto*
	(1)	(2)	(3)	(4)
Δ Robot Exposure	-0.00108***	0.00030	-0.00077	-0.00033
	(0.00030)	(0.00019)	(0.00050)	(0.00055)
Gender	0.02790	0.00508***	0.02992	0.00507***
	(0.02410)	(0.00166)	(0.02551)	(0.00166)
White	-0.03383	-0.00717	-0.02992	-0.00718
	(0.05912)	(0.00438)	(0.06363)	(0.00437)
Age (cf 16-25)				
25-44	-0.02862	-0.01715***	-0.02812	-0.01716***
	(0.04166)	(0.00272)	(0.04260)	(0.00272)
45-65	-0.00995	-0.01768***	-0.01087	-0.01771***
	(0.04526)	(0.00277)	(0.04586)	(0.00277)
Married (cf Single)	-0.05591***	-0.01147***	-0.05611***	-0.01148***
	(0.01729)	(0.00112)	(0.01719)	(0.00112)
Skill Level (cf High-skilled)				
Medium-skilled	-0.01019	0.00237**	-0.00850	0.00237**
	(0.01929)	(0.00110)	(0.01905)	(0.00110)
Low-skilled	-0.00129	0.00822***	0.00010	0.00825***
	(0.03563)	(0.00200)	(0.03710)	(0.00200)
SOC (cf Managerial & Professional)				
Clerical	-0.02805	0.00387**	-0.02940	0.00390**
	(0.01850)	(0.00167)	(0.02441)	(0.00167)
Non-routine Services	0.03032	0.00653***	0.04300	0.00658***
	(0.02357)	(0.00137)	(0.03199)	(0.00136)
Plant Operatives	0.00984	0.01274***	0.01009	0.01287***
	(0.01858)	(0.00230)	(0.02198)	(0.00229)
Routine Services	0.08243	0.00939***	0.09601	0.00944***
	(0.07114)	(0.00256)	(0.08061)	(0.00256)
Firm size (cf <25 employees)				
25-200	-0.03442	-0.00504***	-0.03358	-0.00504***
	(0.03050)	(0.00122)	(0.03430)	(0.00122)
>200	-0.03321	-0.00910***	-0.03077	-0.00909***
	(0.03170)	(0.00147)	(0.03385)	(0.00147)
SOC*Δ Robot Exposure (cf Managerial & Professional)				
Clerical*Δ Robot Exposure			0.00102	0.00055
			(0.00076)	(0.00052)
Non-routine Services*Δ Robot Exposure			-0.00090	0.00082
			(0.00071)	(0.00053)
Plant operatives*Δ Robot Exposure			-0.00008	0.00102*
			(0.00069)	(0.00056)
Routine services*Δ Robot Exposure			-0.00178	0.00096*
			(0.00195)	(0.00055)
Observations	558	65,048	558	65,048
R-squared	0.08656	0.01022	0.08930	0.01027

All specifications include broad-industry-year and region fixed effects. Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

Table A.9. Robustness Checks: Lagged Robot Exposure and Pre & Post 2008

Dependent Variable: Probability of becoming unemployed	*Lagged Robot Exposure (1 year)*	*Lagged Robot Exposure (2 years)*	*Pre 2008*	*Post 2008*
	(1)	(2)	(3)	(4)
_Δ Robot Exposure$_t$			0.00006	-0.00049
			(0.00011)	(0.00052)
_Δ Robot Exposure$_{t-1}$	-0.00032			
	(0.00029)			
_Δ Robot Exposure$_{t-2}$		0.00037		
		(0.00022)		
Gender	0.00508***	0.00569***	0.00294**	0.01043**
	(0.00171)	(0.00177)	(0.00110)	(0.00401)
White	-0.00463	-0.00490	-0.01267*	0.00043
	(0.00425)	(0.00418)	(0.00646)	(0.00373)
Age (cf 16-25)				
25-44	-0.01477***	-0.01141***	-0.01743***	-0.01683*
	(0.00291)	(0.00313)	(0.00260)	(0.00891)
45-65	-0.01459***	-0.01070***	-0.01765***	-0.01624*
	(0.00316)	(0.00346)	(0.00258)	(0.00919)
Married (cf Single)	-0.01092***	-0.01024***	-0.01171***	-0.01207***
	(0.00128)	(0.00121)	(0.00146)	(0.00236)
Skill Level (cf High-skilled)				
Medium-skilled	0.00243**	0.00225**	0.00241*	0.00234
	(0.00115)	(0.00100)	(0.00132)	(0.00197)
Low-skilled	0.00748***	0.00686***	0.00761***	0.00847*
	(0.00205)	(0.00213)	(0.00216)	(0.00474)
SOC (cf Managerial & Professional)				
Clerical	0.00208	0.00206	0.00442**	0.00445
	(0.00176)	(0.00191)	(0.00185)	(0.00365)
Non-routine Services	0.00549***	0.00499***	0.00760***	0.00638
	(0.00130)	(0.00141)	(0.00116)	(0.00386)
Plant Operatives	0.01123***	0.00954***	0.01010***	0.01716***
	(0.00233)	(0.00210)	(0.00276)	(0.00365)
Routine Services	0.00937***	0.00729***	0.00725**	0.01291**
	(0.00248)	(0.00226)	(0.00329)	(0.00457)
Firm size (cf <25 employees)				
25-200	-0.00436***	-0.00367**	-0.00525***	-0.00548*
	(0.00119)	(0.00140)	(0.00132)	(0.00276)
>200	-0.00784***	-0.00695***	-0.01023***	-0.00685***
	(0.00142)	(0.00130)	(0.00213)	(0.00229)
Observations	56,855	48,528	40,208	20,584
R-squared	0.00875	0.00752	0.01096	0.01209

All specifications include broad-industry-year and region fixed effects. Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

Table A.10. Logit Specification

Dependent Variable: Probability of becoming unemployed	(1)	(2)[14]
Δ Robot Exposure	-0.00004	-0.00131
	(0.00010)	(0.00473)
Gender	0.00399***	
	(0.00085)	
White	-0.00543**	
	(0.00220)	
Age (cf 16-25)		
25-44	-0.00889***	-0.12690
	(0.00172)	(0.45582)
45-65	-0.00889***	-0.03350
	(0.00184)	(0.18439)
Married (cf Single)	-0.01054***	-0.03541
	(0.00103)	(0.11579)
Skill Level (cf High-skilled)		
Medium-skilled	0.00251**	0.20685
	(0.00100)	(0.41873)
Low-skilled	0.00673***	0.09523
	(0.00150)	(0.15077)
SOC (cf Managerial & Professional)		
Clerical	0.00386***	0.00269
	(0.00130)	(0.04314)
Non-routine Services	0.00576***	0.01477
	(0.00112)	(0.06025)
Plant Operatives	0.00958***	0.01720
	(0.00178)	(0.07330)
Routine Services	0.00799***	-0.05773
	(0.00223)	(0.13023)
Firm size (cf <25 employees)		
25-200	-0.00395***	-0.05985
	(0.00105)	(0.22843)
>200	-0.00710***	-0.10766
	(0.00105)	(0.32337)
Industry-year FEs	Yes	Yes
Region FEs	Yes	No
Individual FEs	No	Yes
Observations	65,410	6,566
Log-likelihood	-5347.3	-1704.5

Standard errors are clustered at the industry-year level (in parentheses). *** p<0.01, ** p<0.05, * p<0.1

[14] Conditional logit drops observations which have no within-variation for the dependant variable. Thus, all individuals which never experience a transition from employment to unemployment (i.e. the dependent variable is always = 1 and never takes the value of 0) are dropped from the sample.

Table A.11. IV Regressions

Dependent Variable:	**Change in Robot Exposure (UK)**	**Probability of becoming unemployed**
	First-Stage (1)	*Reduced-Form* (2)
Δ **Robot Exposure**$_{ITALY}$	0.39722***	
	(0.00691)	
Δ **Robot Exposure**		0.00003
		(0.00016)
Gender	0.03341***	0.00518***
	(0.01106)	(0.00167)
White	-0.01350	-0.00740*
	(0.02631)	(0.00434)
Age (cf 16-25)		
25-44	0.00864	-0.01707***
	(0.01030)	(0.00267)
45-65	0.00587	-0.01745***
	(0.00923)	(0.00274)
Married (cf Single)	0.00132	-0.01176***
	(0.01532)	(0.00116)
Skill Level (cf High-skilled)		
Medium-skilled	-0.02149	0.00230**
	(0.01609)	(0.00109)
Low-skilled	-0.01677	0.00809***
	(0.01577)	(0.00199)
SOC (cf Managerial & Professional)		
Clerical	-0.01126	0.00384**
	(0.01424)	(0.00167)
Non-routine Services	0.02614*	0.00673***
	(0.01428)	(0.00135)
Plant Operatives	0.02272	0.01269***
	(0.02907)	(0.00228)
Routine Services	-0.01974	0.00967***
	(0.01345)	(0.00258)
Firm size (cf <25 employees)		
25-200	0.03427**	-0.00510***
	(0.01297)	(0.00121)
>200	0.06868***	-0.00898***
	(0.02005)	(0.00147)
Observations	65,606	65,606
R-squared	0.86109	0.00826

All specifications include broad-industry-year and region fixed effects. *** p<0.01, ** p<0.05, * p<0.1