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Neither Left-Behind nor Superstar:

Ordinary Winners of Digitalization at the Ballot Box

Supplementary Information

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1 Description of the Data

1.1 Summary Statistics

Table 1: Summary Statistics

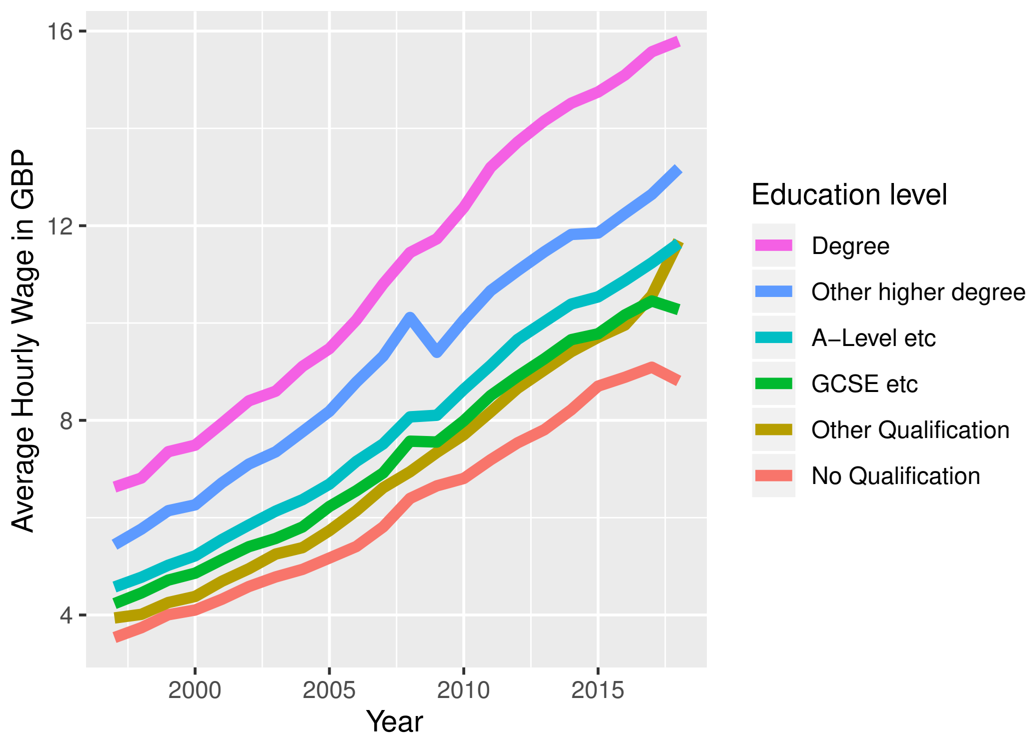
	count	mean	sd	min	max
Year	288009	2009.45	5.40	1997	2018
Turnout	108564	70.71	45.51	0.00	100
Conservatives	233512	22.06	41.47	0.00	100
Labour	233512	32.85	46.97	0.00	100
Liberal Democratic Party	233512	9.60	29.46	0.00	100
UKIP	65914	4.50	20.73	0.00	100
Incumbent	233512	31.20	46.33	0.00	100
Industry ID from EUKELMS.	288009	25.86	9.38	1	38
ICT capital stock (by hours worked)	257241	3.71	4.58	0.10	47.46
Non-ICT capital stock (machinery only)	257241	27.87	44.20	2.20	540.77
Non-ICT capital stock (total)	257241	133.43	392.35	6.46	4955.94
ICT capital stock US (by UK hours worked)	250883	50.28	147.52	0.33	1771.66
Imported goods from China (in 1000 GBP per worker)	40365	9.22	20.77	0.01	189.74
Government region ID	287159	6.96	3.26	1	13
Female	288009	0.50	0.50	0	1
Born outside the UK	288009	0.03	0.17	0	1
Age	288009	40.55	12.07	18	64
Age squared	288009	1789.69	984.46	324	4096
Highest Degree, harmonised	288009	3.08	1.52	0	5
Monthly Net Pay	235955	1357.66	924.85	0	14210
Hourly net wage	201834	9.48	5.39	0	100.8
Probability to become unemployed	225033	2.25	14.83	0	100
Above median RTI	267850	0.47	0.50	0	1
Supports Government Intervention	69004	-0.06	1.03	-3.22	2.90
Social Progressiveness	146729	0.24	1.32	-3.34	3.04
Life Satisfaction	262063	5.22	1.28	1	7
Observations	288009				

Note: ICT defined as "real fixed ICT capital stock (in 1000 GBP or USD, respectively, in constant 2010 prices) normalized by number of employees".

1.2 Dependent Variables by Education

This section presents the longitudinal evolution of our dependent variables between 1997 and 2017, dividing the sample by education level. Figure 1 plots the average net hourly wage. As in the main analysis, we use constant 2010 prices. The wages of all educational groups have increased over time. In the period until the financial crisis, the growth was largely similar for all income groups, but there is a divergence after the crisis between respondents with university degrees and the rest.

Figure 1: Average hourly net wage by education



Note: Hourly net wage calculated as monthly net wage in constant 2010 prices normalized by average hour worked. In 2009, BHPS is changed into US which results in the inclusion of new households into the sample.

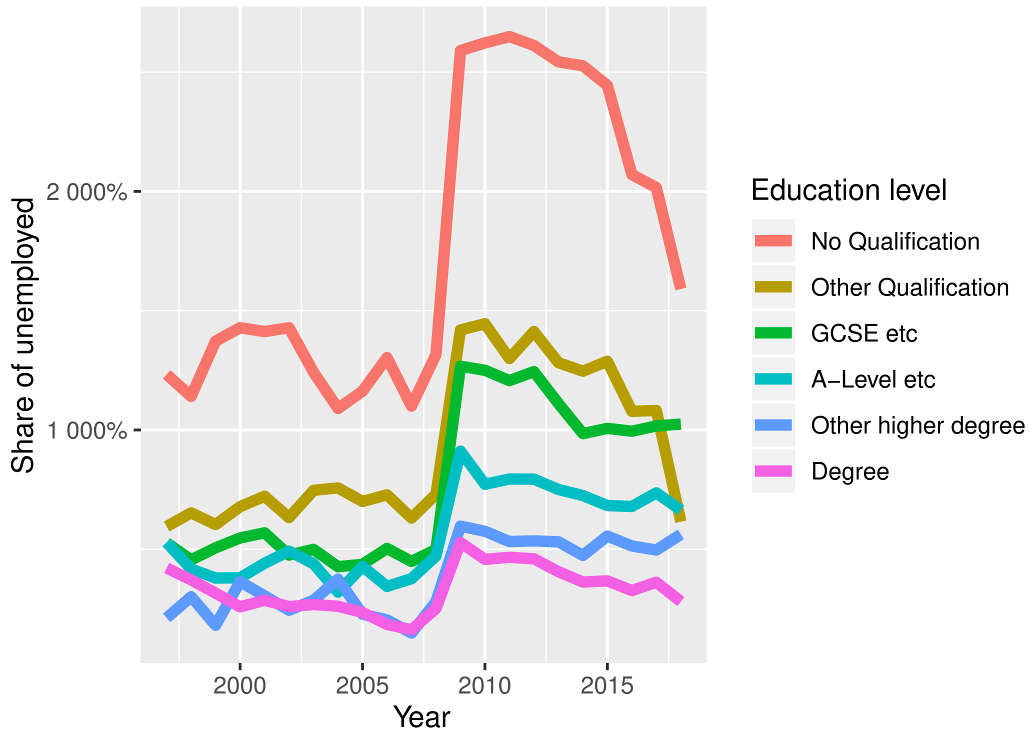
Figure 2 presents the percentage of respondents who were unemployed in the week when the interview was conducted. Here again we observe some divergence, as increases in unemployment after the crisis were particularly visible among citizens with less education. Note that unemployment shares in our actual sample are smaller because those who stay unemployed for two periods are not captured by our operationalization.

Figure 3 describes the probability to become unemployed (i.e. to be unemployed at the time of next interview). Again, we see that less educated respondents are more likely to become unemployed and there is an increase after the financial crisis of 2008.

Figure 4 plots reported turnout for different education levels. Note that this was only asked infrequently after 2008. There was a steady decline in turnout until the mid 2000s and then a partial recovery. Turnout is consistently higher for the highly educated.

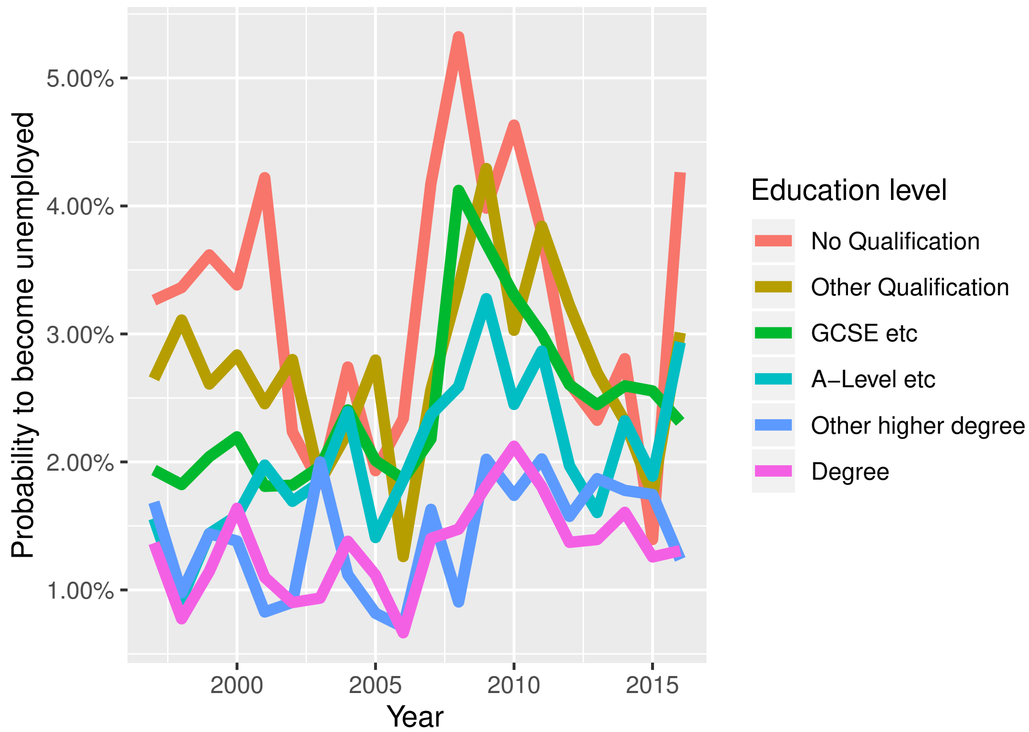
Figure 5 plots the average support for the political parties included in the analyses: the Conservative Party, the Labour Party, as well as the Liberal-Democratic Party, and UKIP (since 2013). We observe a markedly different evolution of support for parties for different education groups, with support for

Figure 2: Share unemployed by education



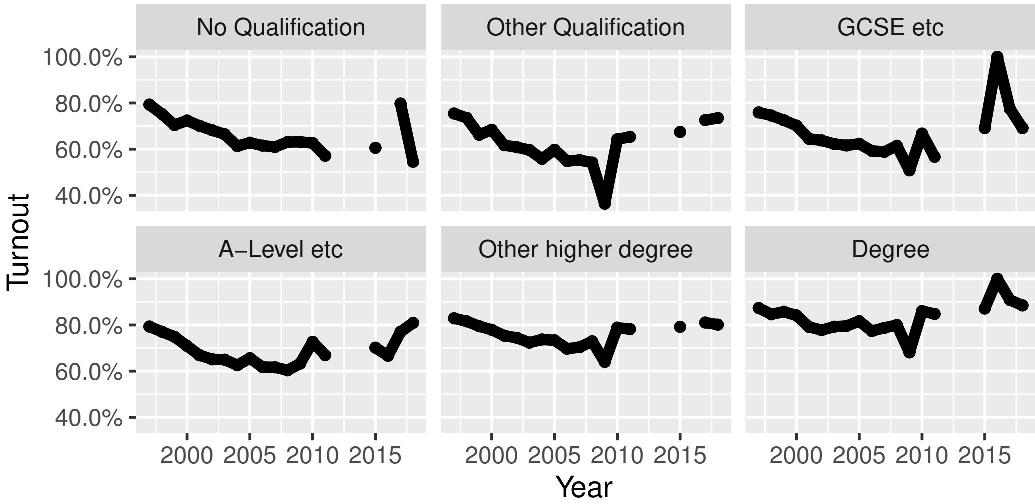
Note: Share unemployed at the time of the interview.

Figure 3: Probability to become unemployed in the next period by education



Note: Average probability to become unemployed in the next interview for different education groups. Currently unemployed and respondents without any industry assignment are excluded to ensure equivalence with the main analysis. In 2009, BHPS is changed into US which results in the inclusion of new households into the sample.

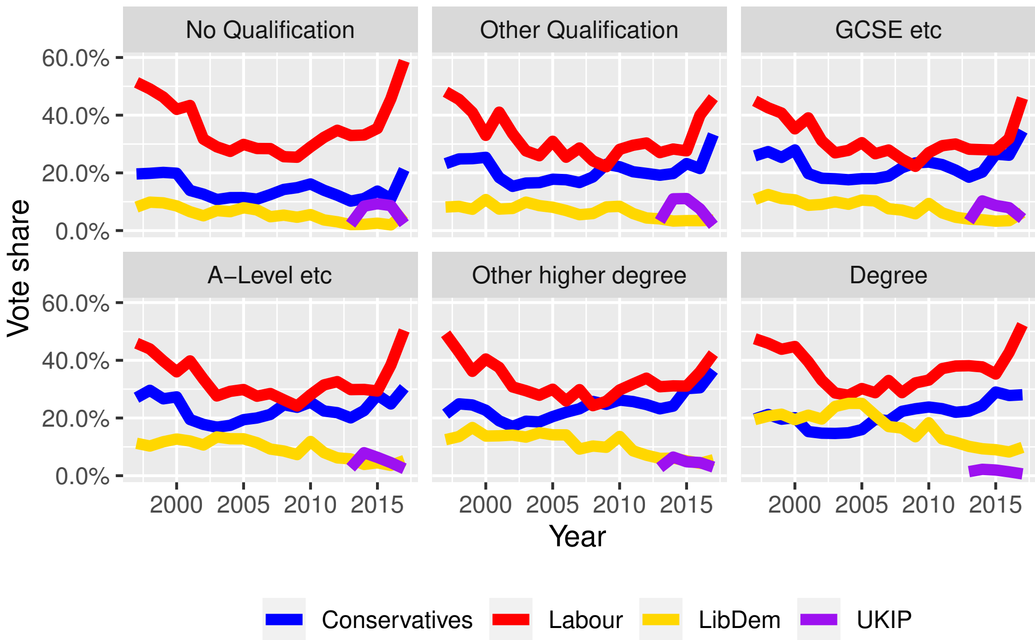
Figure 4: Reported voter turnout by education



Note: Participation in elections was asked in all waves of BHPS which ended in 2008. In the Understanding Society Survey, participation in elections was only asked in 2010, 2015 and to the few participants of the latest wave who were interviewed after the snap-elections of 2017 which makes the group averages less representative of the election turnout of the whole education group. This does not affect our main results as we focus at within-individual variation.

the Conservatives having grown most among workers with university degrees, at the expense of the Liberal-Democratic Party. Some of the time trends will be captured by the year fixed effects.

Figure 5: Support for political parties by education



Note: Vote shares calculated based on sample responses answering they voted for the respective party divided by the number of responses for any party including other parties not reported here.

1.3 Crosswalking and Merging Data Sets

The BHPS, UKHLS and the EU KLEMS datasets are provided using different classifications, which we address by constructing cross-walks. We are able to match the 2007 version of the Standard Industrial Classification (SIC07), used between 2009 and 2015 comprehensively to the classification scheme used by EU KLEMS (NACE Rev. 2). We also manually construct cross-walks from SIC 1992, used in 1994, 1997 and from 2001 to 2008, and are able to match the vast majority of respondents. Between 1991 and 2001 the BHPS used the SIC 1980, which differs markedly from the following versions. We use another crosswalk to translate SIC-80 codes into SIC-92 codes, which then allows to merge the remaining years of EU-KLEMS data. This procedure generates an individual-level data set with information on ICT capital per industry ranging from 1997 to 2017.

2 Comparison of RTI and education as key dimension

In this section, we show that while education is a strong moderator predicting if workers stand to gain or lose from workplace digitalization, RTI seems to be less relevant.

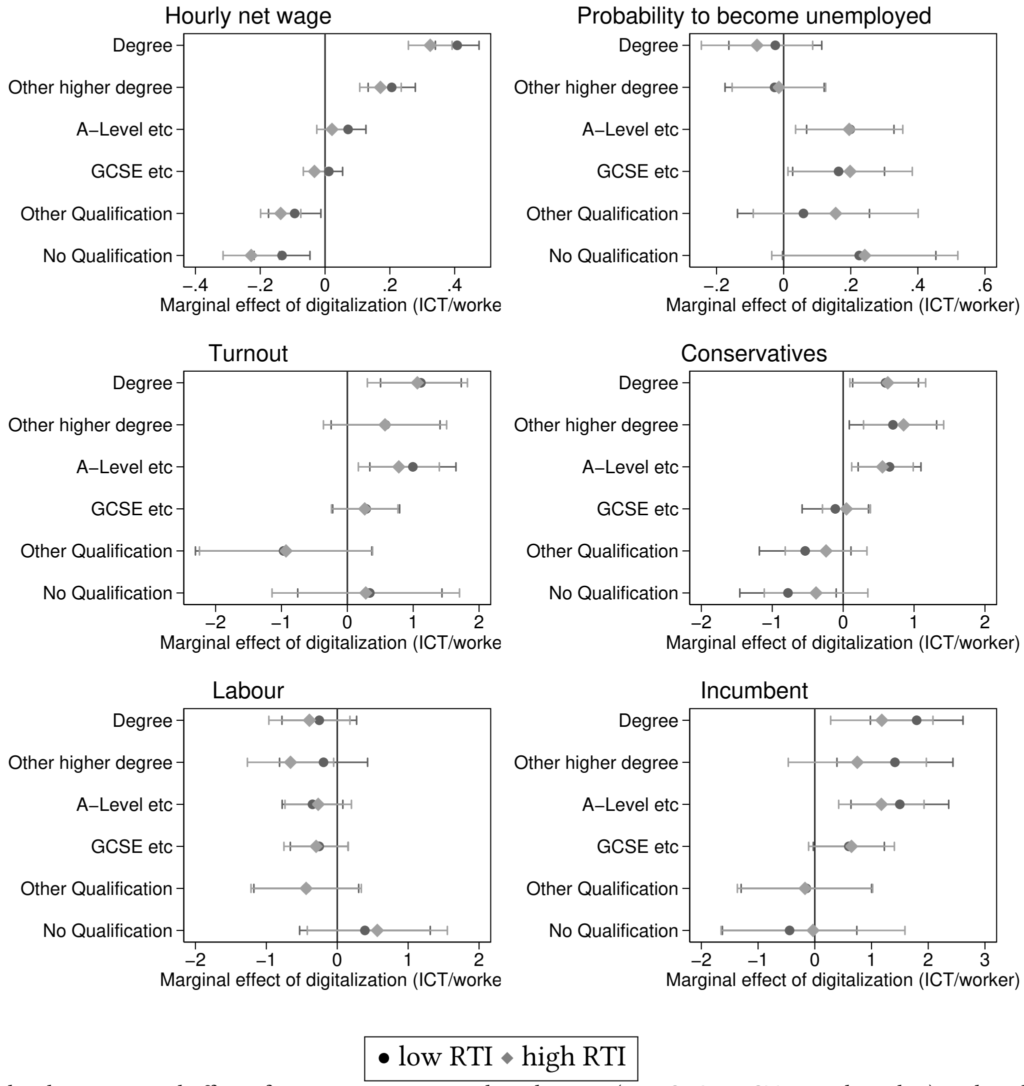
Specifically, we created occupation-specific RTI scores from ONET data following the standard approach of Autor and Dorn (2013), i.e. subtracting log abstract and log manual content from log routine content of each occupation, and relying on a crosswalk by Hardy and colleagues (2018) to merge data with European occupational codes. We then split the observations in high and low RTI groups if they are above or below the median of RTI in the sample.

Figure 6 shows that high RTI workers in general benefit less from digitalization in terms of wages, as we would expect, but the differences are not statistically significant. By contrast, the strong education gradient suggests that digitalization affect highly and less educated workers in very heterogeneous ways. We learn from this analysis that when looking at individual trajectories, education seems to be a more important source of heterogeneity in the impact of digitalization than RTI.

Given the strong emphasis in the economics literature on the distinction between routine and non-routine occupations, this finding is somewhat surprising. However, this literature looks mostly at aggregate level economic outcomes and we discuss in the text several reasons why our within-individual effects may diverge. We believe that education may be a better proxy than RTI for the ability of workers to adapt to and benefit from digitalization. RTI may predict which jobs are more likely to be partially or fully conducted by machines, but it does not predict well if the individual worker performing a job will benefit or lose from digitalization. The difference between the aggregate level and micro level results are worth further empirical exploration.

In any case, the empirical findings reported here are a strong motivation for our decision of concentrating on education as the key moderator of the effects of workplace digitalization on economic and political outcomes.

Figure 6: Main outcomes split by high and low RTI



Note: Results show marginal effect of one unit increase in digitalization (1000GBP in ICT capital/worker) on hourly wage, probability to become unemployed and probability to report to have voted or support a given political party. All results except for the hourly wage are in percentage points. High RTI and low RTI is defined relative to the median RTI of the sample.

3 Economic Effects Before and After the 2010 Government Change

Table 2 shows a sub-period analysis for our economic outcomes. It compares the results for hourly net wages and the probability to become unemployed for the time before and after the government change in 2010. The results are comparable to the composite effects. The main difference seems to be that in the 2010 onward period, low educated workers do not appear to lose out in terms of wages in absolute term when they were effected by digitalization. Nevertheless, digitalization decreased their relative wage performance as the effect of digitalization on the wages of the higher educated increases over time.

Table 2: Economic effects pre and post Government change in May 2010

	Hourly Wage		Unemployment	
	(1)	(2)	(3)	(4)
	Pre May 2010	Post May 2010	Pre May 2010	Post May 2010
Degree × ICT	0.325***	0.315***	-0.0582	0.0758
	(0.0351)	(0.0486)	(0.113)	(0.124)
Other higher degree × ICT	0.165***	0.215***	-0.142	0.0521
	(0.0481)	(0.0438)	(0.0923)	(0.140)
A-Level etc × ICT	0.0459	0.107*	0.235*	0.315*
	(0.0270)	(0.0425)	(0.111)	(0.147)
GCSE etc × ICT	-0.0324	0.0953*	0.218*	0.174
	(0.0215)	(0.0393)	(0.101)	(0.173)
Other Qualification × ICT	-0.117**	-0.00711	0.152	0.0615
	(0.0376)	(0.0613)	(0.137)	(0.210)
No Qualification × ICT	-0.206***	-0.0325	0.247	0.346
	(0.0490)	(0.0692)	(0.139)	(0.235)
Age	0.339***	0.479***	-0.173	-0.222
	(0.0287)	(0.0484)	(0.135)	(0.203)
Age × Age	-0.00299***	-0.00423***	-0.000419	0.00142
	(0.000261)	(0.000329)	(0.000960)	(0.00133)
Individual*Industry FE	X	X	X	X
Education Level FE	X	X	X	X
Year FE	X	X	X	X
Region	X	X	X	X
Observations	85797	93713	100647	115580

Note: All columns use our main specification. Column (1) and (2) report a sub-period analysis for net hourly wages (calculated as monthly net wage in constant 2010 prices normalized by average hour worked. Column (3) and (4) report a sub-period analysis for probability to become unemployed in percentage points (ie. to be unemployed at the next interview conditional on currently working). Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4 Robustness Checks in Detail

This section extends the discussion about the robustness checks offered in the main body of the text. The full regression tables are presented at the end of this section.

4.1 Non-ICT capital investment

First, we need to rule out the possibility that an increase in ICT capital stocks simply reflects the fact that booming industries have a larger capacity to invest and offer their workers higher wages and better conditions. If the general propensity to invest of a sector has an effect on workers' economic outcomes and political preferences, this could invalidate our interpretation of our results. They would not capture the specific consequences of digitalization but rather the effect of working in a thriving industry.

To assess this possibility, we conduct an additional analysis using non-ICT capital stock per worker as the main explanatory variable:

$$\text{Non-ICT capital intensity}_{jt} = \frac{\text{Total capital stock}_{jt} \text{ - ICT capital stock}_{jt}}{(\text{Employees}_{jt})}$$

Changes in an industry's non-ICT capital stock do not predict any of the outcomes we are interested in. As can be seen in column (3) in the tables presented in this section, the coefficients are very small and imprecisely estimated. This was to be expected since we argued that investment in digitalization substitutes or complements labor in a specific way depending on their skill level. The same is not true for other kinds of capital investments (e.g. building a new production plant or buying a new office building).

This result increases our confidence in the interpretation that the main results are driven specifically by ICT capital, since other kinds of capital do not affect workers' political preferences in a similar way.

In addition, we have tested more specific aggregations of residual asset categories among the non-ICT group. Certain asset categories we categorize as non-ICT but might not be seen as "digital" assets but still relate to technological change more broadly, e.g. other machinery equipment besides ICT equipment. As we argue in the manuscript, our goal is to specifically study the impact of digitalization, not the impact of the broader and more elusive concept of technological change. That said, since the data allows for more fine-grained analysis, we have explored further operationalizations to examine implications for the presented main results. We replicated our analysis with a dependent variable consisting only of the two categories related to non-digital machinery ("transportation", "other machinery equipment and weapons"). We find that investment in machinery has somewhat comparable economic effects in that it has positive wage implications on high-skilled workers. However, crucially, the effect sizes are much smaller than the effects of ICT investment. In terms of standard deviations, a one standard deviation in ICT capital stocks produces an increase of 0.25 GBP per hour worked among workers with university degrees, but non-ICT machinery only translates into an increase of 0.05 GBP per hour. Consequently, and unsurprisingly, these much smaller effects do not translate into changes in workers' political behavior. In line with the original non-ICT analysis, we do not find any evidence that investment in machinery affects political outcome variables.

4.2 Excluding industry and regional outliers

One might object that our results could be driven by a few rapidly digitalizing industries. To rule out this possibility, we excluded the three industries with the largest increase in digitalization in recent years (Telecommunications, Mining and Quarrying and Coke, Refined petroleum) in the models in column (4). The exclusion of these outliers does not change results. If anything, it even increases the precision of our estimates.

Relatedly, our results could also be driven by some particularly rapidly digitalizing regions such as the metropolitan area of London. To account for this, we include separate set of time fixed effects for each region. Column (5) in below tables confirms that the results are not driven by these regions, as point estimates remain largely unchanged for all outcomes while standard errors decrease for some outcomes.

4.3 Lead models and simple fixed effects

Another key concern is that our models are too restrictive towards losers and thus may underestimate the effects of digitalization because they miss the negative effects on workers who are displaced by digitalization and do not work in the same industry in the next period when they are re-interviewed. This could happen for two different reasons. If displaced workers drop out of the labor force they would not be assigned to an industry in the next interview and would therefore drop out of our analysis. If they switch to a different industry, the industry-spell fixed effects would absorb part of the effect of job displacement on economic and political outcomes. In any case, our models may fail to capture the effects of digitalization on some displaced workers workers.

We deal with this concern by relaxing the sample restriction in two ways and thus potentially capturing more losers: First, we replicate all analyses using lead models in which we examine how our measure of digitalization affects labor market and political outcomes measured at the time of the next interview. In this way, we keep in our sample all workers who may have been displaced by digitalization (and either exit the labor force or work in a different industry). This results in a slightly smaller sample (because we lose the last year), but the coefficients reported in column (6) confirm that the results remain unchanged when using leads. The only exception is voter turnout, as several of the coefficients of interest become statistically non-significant.

Second, we replicate all analyses using a unique individual fixed effect by respondent instead of industry-spell fixed effects. Using this approach, workers who change industries (perhaps in response to job displacement due to technology) contribute to the average estimates of the effect of digitalization on labor market and political outcomes, although workers who drop out of the labor force entirely are still excluded from the sample. The results are reported in column (7) in the full tables below. Although the polarizing effect of digitalization on wages is still clearly visible, this specification results in smaller estimates of the effects of digitalization on hourly pay for both highly and less educated workers. This was to be expected as using unique individual fixed effects adds measurement error to our explanatory variable which causes attenuation bias in the estimated coefficients.[1] An alternative explanation is that economic benefits of digitalization are reaped mostly by educated workers who stay in their industries while the costs may be borne also by less educated workers who choose to stay in the same industries.

[1]The variation in digitalization created by industry switches is much larger than the year to year variation for stayers which is problematic for two reasons. First, frequent back and forth switches between two industries within individuals is possibly due to measurement error in the interviews. Second, we theorize that a digitalizing workplace is what affects political attitudes, not the jumps when switching between highly and low digitalized industries.

Using this specification, we do not find effects of digitalization on voter turnout, but we still observe that digitalization is associated with increased support for the Conservatives and the incumbent party among workers with more education.

4.4 Including controls for trade

A possible threat to identification is that our indicator of technology may be correlated with changes in international trade in an industry. In that case, our estimates would partially capture effects of international trade on economic outcomes and political behavior. However, previous work on the geography of trade shocks and technological change in the US shows that the two types of shocks have largely distinct distributions in space (Autor et al., 2015), suggesting that there is limited overlap. In any case, we replicate all the analysis controlling for international trade in the industries for which we can collect data. Specifically, we use yearly UN Comtrade data on exports from China to the UK as an indicators of international trade.[2] This measure is only available for manufacturing industries, resulting in a much smaller sample size. The results presented in column (8) of the complete tables show that the results remain substantively similar (but less precisely estimated) when controlling for changes in trade within the industries for which data are available.

4.5 Cross-sectional OLS

For the sake of completeness, we also add a cross-sectional OLS regression including only industry and year fixed effects to see how between-worker differences in ICT intensity relate to our outcomes (column 9). Results have to be interpreted with a large grain of salt as we now cannot control for unobserved worker-level characteristics anymore. Instead, except for the inclusion of a gender dummy, we tried to stay as close as possible to our main specification to ensure the comparability of results while avoiding post-treatment bias. The results for political outcomes are surprisingly similar to the fixed-effects specification. Especially, they confirm the finding that digitalization increase support for the Conservatives for the incumbent among highly educated workers.

Regarding economic outcomes, the results change slightly. The highly educated are still the main beneficiaries when it comes to wages. However, looking at unemployment, less educated people already

[2] The data is provided for different types of goods which we first crosswalk to SIC and from there to NACE rev. 2 codes which is used in EUKLEMS.

working in digitalized industries appear to benefit from digitalization as they have lower probabilities to become unemployed. This is somewhat counter-intuitive and seemingly opposite to our findings from the baseline specification. Yet, the two diverging results make sense considering the different nature of the two analyses. The cross-sectional analysis shows that working in an already digitalized industry reduces the risk of unemployment whereas the fixed-effects specification shows that for a given worker in a given industry, increasing digitalization might threaten the jobs of less educated workers if tasks are automated. We interpret this more nuanced reading as a validation that it is important to only consider within-individual variation if we want to study how a *given worker* is affected when his or her work environment digitalizes.

Table 3: Net hourly wages in GBP

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	0.345***	0.437***	-0.000770	0.333***	0.435***	0.303***	0.155***	0.486***	0.134***
	(0.0323)	(0.0805)	(0.000710)	(0.0306)	(0.0409)	(0.0362)	(0.0161)	(0.0816)	(0.00869)
Other higher degree × ICT	0.185***	0.306***	-0.000465	0.183***	0.222***	0.170***	0.108***	0.344***	0.105***
	(0.0338)	(0.0747)	(0.000542)	(0.0333)	(0.0430)	(0.0338)	(0.0165)	(0.0638)	(0.00921)
A-Level etc × ICT	0.0497*	0.104	-0.000714	0.0479*	0.0814*	0.0605*	0.0721***	0.117*	0.131***
	(0.0230)	(0.0859)	(0.000452)	(0.0227)	(0.0362)	(0.0254)	(0.0143)	(0.0539)	(0.00787)
GCSE etc × ICT	-0.0113	-0.0439	-0.000710	-0.0141	-0.00472	-0.0110	0.0462***	0.00887	0.114***
	(0.0185)	(0.0596)	(0.000435)	(0.0184)	(0.0283)	(0.0209)	(0.0130)	(0.0419)	(0.00808)
Other Qualification × ICT	-0.135***	-0.222*	-0.00109*	-0.141***	-0.146***	-0.127***	0.0318	-0.0934	0.0981***
	(0.0290)	(0.0873)	(0.000501)	(0.0288)	(0.0348)	(0.0307)	(0.0176)	(0.0610)	(0.0105)
No Qualification × ICT	-0.185***	-0.306***	-0.00127**	-0.188***	-0.211***	-0.123**	-0.00718	-0.230*	0.0359**
	(0.0399)	(0.0877)	(0.000446)	(0.0391)	(0.0503)	(0.0420)	(0.0210)	(0.0998)	(0.0113)
Age	0.356***	0.357***	0.401***	0.385***	0.354***	0.357***	0.374***	0.236***	0.446***
	(0.0272)	(0.0279)	(0.0281)	(0.0276)	(0.0273)	(0.0315)	(0.0263)	(0.0587)	(0.00527)
Age × Age	-0.00316***	-0.00314***	-0.00334***	-0.00319***	-0.00311***	-0.00344***	-0.00337***	-0.00187***	-0.00454***
	(0.000213)	(0.000221)	(0.000218)	(0.000213)	(0.000213)	(0.000240)	(0.000191)	(0.000431)	(0.0000677)
Imports								-0.00255	
								(0.00333)	
Female									-1.192***
									(0.0210)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	179510	174751	179510	179510	176693	153834	178501	32833	179510

Note: Hourly net wage calculated as monthly net wage in constant 2010 prices normalized by average hours worked. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Probability to become unemployed

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	0.00423	0.206	-0.000245	0.00656	-0.0919	0.177	0.0683	-0.0913	0.0230
	(0.0711)	(0.197)	(0.000640)	(0.0708)	(0.0809)	(0.103)	(0.0450)	(0.101)	(0.0248)
Other higher degree × ICT	0.00105	0.215	-0.000141	0.00980	-0.0737	0.0820	0.0826	-0.153	0.0277
	(0.0654)	(0.257)	(0.000618)	(0.0655)	(0.102)	(0.0780)	(0.0707)	(0.146)	(0.0291)
A-Level etc × ICT	0.175**	0.398	0.000127	0.187**	0.156*	0.134	0.172**	0.134	0.0261
	(0.0592)	(0.206)	(0.000709)	(0.0597)	(0.0671)	(0.0928)	(0.0531)	(0.142)	(0.0283)
GCSE etc × ICT	0.177**	0.539	-0.000185	0.181**	0.150	0.260**	0.113*	0.131	0.00738
	(0.0679)	(0.412)	(0.000668)	(0.0678)	(0.0898)	(0.0859)	(0.0520)	(0.136)	(0.0298)
Other Qualification × ICT	0.0941	0.529	-0.000163	0.0970	0.0273	0.000882	-0.00295	-0.161	-0.00626
	(0.0856)	(0.279)	(0.00124)	(0.0857)	(0.0919)	(0.110)	(0.0893)	(0.285)	(0.0446)
No Qualification × ICT	0.256*	0.608	-0.000124	0.254*	0.261	0.248	-0.0199	0.112	-0.0474
	(0.104)	(0.446)	(0.00113)	(0.104)	(0.134)	(0.156)	(0.0893)	(0.171)	(0.0472)
Age	-0.367***	-0.367***	-0.361***	-0.365***	-0.373***	-0.155	-0.529***	-0.280	-0.471***
	(0.101)	(0.103)	(0.104)	(0.104)	(0.101)	(0.111)	(0.110)	(0.272)	(0.0239)
Age × Age	0.00158**	0.00168**	0.00153*	0.00155*	0.00153*	0.00237**	0.00424***	0.00255	0.00494***
	(0.000603)	(0.000623)	(0.000601)	(0.000603)	(0.000605)	(0.000731)	(0.000610)	(0.00171)	(0.000275)
Imports								0.00663	
								(0.0140)	
Female									-0.521***
									(0.0750)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	216227	210803	216227	216227	213177	183337	214834	34845	216227

Note: Probability to become unemployed in percentage points among those currently working. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Voted in last general elections

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	0.797**	1.376*	0.00907	0.708**	1.050**	0.273	0.379*	0.572	0.00923
	(0.272)	(0.620)	(0.00533)	(0.269)	(0.377)	(0.286)	(0.151)	(0.738)	(0.109)
Other higher degree × ICT	0.340	2.090*	0.00751	0.326	0.799	0.694	0.258	0.155	-0.148
	(0.357)	(1.058)	(0.00453)	(0.355)	(0.541)	(0.389)	(0.188)	(0.627)	(0.132)
A-Level etc × ICT	0.713**	2.013*	0.00616	0.716**	0.973**	1.100***	0.463**	0.415	0.188
	(0.258)	(1.025)	(0.00638)	(0.262)	(0.367)	(0.286)	(0.153)	(0.524)	(0.116)
GCSE etc × ICT	0.243	1.211	-0.00198	0.216	-0.248	0.346	0.339*	0.101	0.171
	(0.229)	(0.986)	(0.00516)	(0.227)	(0.395)	(0.259)	(0.156)	(0.492)	(0.119)
Other Qualification × ICT	-0.815	1.994	-0.00557	-0.864	-0.695	-0.288	0.295	-1.938	-0.376*
	(0.571)	(1.860)	(0.00751)	(0.570)	(0.556)	(0.427)	(0.252)	(1.248)	(0.181)
No Qualification × ICT	0.147	2.198	0.00179	0.195	0.249	0.706	0.594*	-1.219	0.332
	(0.469)	(3.152)	(0.00556)	(0.468)	(0.673)	(0.493)	(0.271)	(0.806)	(0.189)
Age	-1.126**	-1.041*	-0.434	-0.485	-1.170**	0.286	-0.970**	-2.427*	1.957***
	(0.392)	(0.405)	(0.399)	(0.399)	(0.396)	(0.396)	(0.360)	(0.948)	(0.0801)
Age × Age	-0.00836**	-0.00891**	-0.00910***	-0.00872***	-0.00791**	-0.00910***	-0.00857***	0.000698	-0.0111***
	(0.00266)	(0.00291)	(0.00265)	(0.00265)	(0.00268)	(0.00271)	(0.00231)	(0.00640)	(0.000958)
Imports								-0.0620	
								(0.0618)	
Female									0.215
									(0.302)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	103755	100893	103755	103755	102075	91405	102652	19196	103755

Note: Probability to report to have voted in last general election in percentage point. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Support for the Conservative Party

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	0.569**	2.157**	0.00359	0.512**	0.758**	0.538**	0.351***	1.231	0.280***
	(0.196)	(0.674)	(0.00276)	(0.195)	(0.276)	(0.200)	(0.100)	(0.634)	(0.0727)
Other higher degree × ICT	0.549*	1.727*	0.00732*	0.503*	0.953**	0.814**	0.148	-0.0490	0.0817
	(0.248)	(0.695)	(0.00336)	(0.247)	(0.312)	(0.261)	(0.126)	(0.559)	(0.0837)
A-Level etc × ICT	0.564**	1.443*	0.00677*	0.520**	1.063***	0.623**	0.279**	0.387	0.128
	(0.193)	(0.586)	(0.00300)	(0.189)	(0.275)	(0.198)	(0.101)	(0.348)	(0.0754)
GCSE etc × ICT	-0.0451	0.934	0.000908	-0.0886	0.428	0.151	0.167	-1.081**	0.204*
	(0.192)	(0.657)	(0.00294)	(0.189)	(0.253)	(0.179)	(0.109)	(0.396)	(0.0791)
Other Qualification × ICT	-0.351	1.431	-0.00394	-0.448	-0.227	-0.278	0.0435	-0.730	-0.102
	(0.269)	(0.994)	(0.00569)	(0.277)	(0.329)	(0.254)	(0.142)	(0.537)	(0.108)
No Qualification × ICT	-0.558*	0.494	-0.00131	-0.534	-0.576	-0.337	-0.227	-1.050	-0.244*
	(0.276)	(1.072)	(0.00422)	(0.275)	(0.344)	(0.269)	(0.159)	(0.821)	(0.111)
Age	0.365	0.332	0.603**	0.561*	0.357	0.104	0.235	0.891	0.144**
	(0.224)	(0.230)	(0.228)	(0.228)	(0.225)	(0.235)	(0.206)	(0.572)	(0.0480)
Age × Age	-0.00334*	-0.00279	-0.00359*	-0.00319	-0.00304	-0.00423*	-0.00147	-0.00551	0.00278***
	(0.00164)	(0.00170)	(0.00163)	(0.00163)	(0.00165)	(0.00178)	(0.00140)	(0.00422)	(0.000596)
Imports								0.0149	
								(0.0276)	
Female									-0.111
									(0.192)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	221033	215766	221033	221033	218050	189117	219768	34592	221033

Note: Probability to report to support the Conservative Party in percentage point. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Support for the Labour Party

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	-0.191	0.359	-0.00315	-0.200	-0.0414	-0.0453	-0.179	-0.924	-0.453***
	(0.214)	(0.529)	(0.00332)	(0.212)	(0.280)	(0.212)	(0.103)	(0.849)	(0.0802)
Other higher degree × ICT	-0.180	0.266	-0.00247	-0.185	-0.182	-0.263	0.0653	-0.668	-0.225*
	(0.243)	(0.662)	(0.00358)	(0.247)	(0.322)	(0.326)	(0.119)	(0.443)	(0.0911)
A-Level etc × ICT	-0.227	-0.520	-0.00463	-0.211	-0.469	-0.295	-0.212	-0.281	-0.409***
	(0.190)	(0.529)	(0.00402)	(0.189)	(0.273)	(0.211)	(0.109)	(0.589)	(0.0827)
GCSE etc × ICT	-0.194	0.502	-0.00481	-0.185	-0.484	-0.322	-0.195	0.659	-0.588***
	(0.188)	(0.599)	(0.00417)	(0.188)	(0.266)	(0.182)	(0.115)	(0.568)	(0.0885)
Other Qualification × ICT	-0.502	0.584	-0.00578	-0.485	-0.807*	-0.283	0.0257	0.746	-0.296*
	(0.349)	(0.971)	(0.00725)	(0.347)	(0.410)	(0.338)	(0.167)	(0.712)	(0.120)
No Qualification × ICT	0.417	0.248	-0.00668	0.372	0.312	-0.117	0.247	0.605	-0.0502
	(0.391)	(1.759)	(0.00389)	(0.389)	(0.512)	(0.450)	(0.221)	(0.544)	(0.149)
Age	0.0827	0.174	0.0108	0.0301	0.0530	0.0124	0.188	-1.047	0.542***
	(0.272)	(0.280)	(0.277)	(0.277)	(0.274)	(0.290)	(0.254)	(0.693)	(0.0545)
Age × Age	-0.00413*	-0.00496**	-0.00389*	-0.00405*	-0.00418*	-0.0000333	-0.00478**	0.00376	-0.00616***
	(0.00182)	(0.00191)	(0.00181)	(0.00182)	(0.00183)	(0.00198)	(0.00158)	(0.00436)	(0.000664)
Imports								-0.0241	
								(0.0353)	
Female									-1.526***
									(0.215)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	221033	215766	221033	221033	218050	189117	219768	34592	221033

Note: Probability to report to support the Labour Party in percentage point. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Support for the Incumbent

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	1.536***	2.917*	0.0123	1.425***	2.513***	1.286***	0.960***	0.440	0.865***
	(0.336)	(1.446)	(0.00729)	(0.324)	(0.500)	(0.365)	(0.172)	(0.809)	(0.0835)
Other higher degree × ICT	1.199*	2.361*	0.00926	1.180**	2.329***	1.254*	0.835***	0.318	0.754***
	(0.504)	(1.181)	(0.00595)	(0.456)	(0.600)	(0.554)	(0.219)	(1.121)	(0.0943)
A-Level etc × ICT	1.337***	2.745**	0.00327	1.261***	2.148***	1.074**	0.832***	-0.593	0.729***
	(0.353)	(0.940)	(0.00564)	(0.330)	(0.438)	(0.392)	(0.190)	(0.805)	(0.0855)
GCSE etc × ICT	0.686*	2.109*	0.0000369	0.636*	1.262**	0.831*	0.523**	-0.104	0.546***
	(0.298)	(0.950)	(0.00594)	(0.285)	(0.475)	(0.330)	(0.181)	(0.612)	(0.0909)
Other Qualification × ICT	-0.275	2.750	-0.0158	-0.558	-0.183	-0.304	0.711**	-1.459	0.558***
	(0.535)	(1.757)	(0.00841)	(0.545)	(0.654)	(0.533)	(0.253)	(1.235)	(0.121)
No Qualification × ICT	-0.213	0.560	-0.0230*	-0.308	-0.0251	-0.350	0.546	-0.240	0.139
	(0.564)	(2.137)	(0.0104)	(0.569)	(0.749)	(0.610)	(0.297)	(0.790)	(0.146)
Age	-0.968*	-0.930*	-0.633	-0.751	-1.082**	-1.644***	-1.081**	-1.938	0.391***
	(0.409)	(0.418)	(0.409)	(0.409)	(0.412)	(0.450)	(0.390)	(1.023)	(0.0548)
Age × Age	0.0000293	0.000657	-0.000517	0.000508	0.000901	0.00295	0.000259	0.000620	-0.00193**
	(0.00317)	(0.00325)	(0.00308)	(0.00309)	(0.00318)	(0.00357)	(0.00279)	(0.00819)	(0.000673)
Imports								-0.144	
								(0.0774)	
Female									0.461*
									(0.217)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	221033	215766	221033	221033	218050	189117	219768	34592	221033

Note: Probability to report to support the incumbent in percentage point. Until May 2010, Labour is coded as the incumbent whereas the Conservatives after 2010. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.6 Panel Attrition

Attrition is a key concern in panel data analysis. In our case, one may worry that digitalization causes differential attrition rates between winners and losers. For instance, workers displaced by digitalization can be more likely to move and become more difficult to be located for reinterview. In addition, as discussed above, displacement may force workers to change industries. Higher attrition rates and more industry switches would both make it difficult for us to capture the adverse effects of digitalization, painting an exceedingly optimistic picture.

To examine if digitalization in an industry predicts sample attrition and industry switches, table 9 first presents the results of regressing the likelihood of dropping out of the sample or changing industries on ICT capital per worker. Next, we examine if these effects are heterogeneous for workers with different education levels by regressing both outcomes on the education dummies and the interaction of ICT capital per worker and education.

The results are reassuring as we do not find clear evidence that ICT capital per worker is associated with increased attrition. While the average effect of our key measure of digitalization is in fact negative, suggesting that workers in rapidly digitalizing industries are less likely to drop out of the panel, this difference is very small. Second, digitalization is not clearly associated with a stronger likelihood to change to a different industry in the next period for none of the education groups. In sum, differences between groups are small. It thus seems unlikely that differential attrition is driving our main results.

Table 9: Predictors of attrition

	Leave sample		Change industry	
	(1)	(2)	(3)	(4)
ICT	-0.000641**		0.000162	
	(0.000208)		(0.000207)	
Degree × ICT		-0.00110		0.000561
		(0.00188)		(0.00177)
Other higher degree × ICT		0.00297		-0.00111
		(0.00229)		(0.00204)
A-Level etc × ICT		0.00236		0.000758
		(0.00187)		(0.00157)
GCSE etc × ICT		0.00405*		0.00161
		(0.00184)		(0.00147)
Other Qualification × ICT		0.00410		-0.00161
		(0.00315)		(0.00341)
No Qualification × ICT		0.00838*		0.00775
		(0.00390)		(0.00412)
Age		0.0435***		-0.0212***
		(0.00373)		(0.00287)
Age × Age		-0.000167***		0.000142***
		(0.0000182)		(0.0000182)
Individual*Industry FE	X	X	X	X
Education Level FE		X		X
Year FE	X	X	X	X
Region	X	X	X	X
Observations	234661	234661	200626	200626

Note: Column (1) reports the direct effect of ICT intensity on probably to leave the sample. Column (2) reports the effect of ICT intensity on the probability to leave the sample by education group. Column (3) reports the direct effect of ICT on the probably to change industries. Column (4) reports the effect of ICT on the probably to change industries by education group. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.7 Alternative Clustering

Table 10 shows that our results are robust when we cluster standard errors at the industry-year level rather than the individual level. This table shows that when clustering at the industry-year level, standard errors tend to be somewhat smaller than in the results presented in the main text.

Table 10: All Outcomes with Standard Errors Clustered at the Industry-Year Level

	(1) Hourly wage	(2) Unemployed	(3) Turnout	(4) Conservative	(5) Labour	(6) Incumbent
Degree × ICT	0.345***	0.00423	0.797***	0.569**	-0.191	1.536***
	(0.0362)	(0.0875)	(0.236)	(0.173)	(0.167)	(0.368)
Other higher degree × ICT	0.185***	0.00105	0.340	0.549**	-0.180	1.199***
	(0.0299)	(0.0793)	(0.332)	(0.206)	(0.210)	(0.327)
A-Level etc × ICT	0.0497**	0.175*	0.713**	0.564**	-0.227	1.337***
	(0.0173)	(0.0690)	(0.257)	(0.171)	(0.161)	(0.339)
GCSE etc × ICT	-0.0113	0.177*	0.243	-0.0451	-0.194	0.686*
	(0.0166)	(0.0816)	(0.291)	(0.192)	(0.173)	(0.280)
Other Qualification × ICT	-0.135***	0.0941	-0.815	-0.351	-0.502	-0.275
	(0.0263)	(0.102)	(0.606)	(0.245)	(0.341)	(0.420)
No Qualification × ICT	-0.185***	0.256*	0.147	-0.558*	0.417	-0.213
	(0.0373)	(0.103)	(0.479)	(0.222)	(0.312)	(0.469)
Age	0.356***	-0.367***	-1.126**	0.365	0.0827	-0.968**
	(0.0269)	(0.108)	(0.422)	(0.226)	(0.293)	(0.371)
Age × Age	-0.00316***	0.00158*	-0.00836**	-0.00334*	-0.00413*	0.0000293
	(0.000191)	(0.000711)	(0.00281)	(0.00157)	(0.00176)	(0.00221)
Individual*Industry FE	X	X	X	X	X	X
Education Level FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
Observations	179510	216227	103755	221033	221033	221033

Note: All columns use the main specification. Column (1) reports the results for hourly wage, column (2) for the probability to become unemployed, column (3) for voter turnout, column (4) for vote for the Conservatives, column (5) for vote for Labour and column (6) for vote for the incumbent. Except for the the wage variable, all results in percentage points. Standard error reported in parenthesis are clustered at the industry-year level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.8 Excluding Migrants

Last but not least, we dealt with the concern that migrants affected our results in a systematic way as they might have a different reaction to digitalization when it comes to political preferences. For example, workers with a migration background might be less inclined to turn to the UK Independence Party if they feel left behind by workplace digitalization.

For this reason, we replicate the analyses excluding workers who were born outside of the UK. This reduces the sample size by about 5%. Table 11 shows the results for our main outcomes and the support for UKIP. They are almost indistinguishable from the presented results in the main body of the text.

Table 11: All Outcomes Excluding Foreign-Born Workers

	(1) Hourly wage	(2) Unemployed	(3) Turnout	(4) Conservative	(5) Labour	(6) Incumbent	(7) UKIP
Degree × ICT	0.343***	0.00307	0.786**	0.565**	-0.196	1.546***	-0.437
	(0.0326)	(0.0721)	(0.272)	(0.197)	(0.215)	(0.339)	(0.341)
Other higher degree × ICT	0.186***	-0.00596	0.343	0.532*	-0.172	1.199*	-0.340
	(0.0340)	(0.0672)	(0.357)	(0.249)	(0.244)	(0.507)	(1.034)
A-Level etc × ICT	0.0481*	0.176**	0.709**	0.544**	-0.240	1.311***	-0.890
	(0.0230)	(0.0609)	(0.258)	(0.193)	(0.191)	(0.355)	(0.459)
GCSE etc × ICT	-0.0121	0.176*	0.247	-0.0348	-0.221	0.708*	0.0295
	(0.0185)	(0.0690)	(0.229)	(0.193)	(0.189)	(0.299)	(0.642)
Other Qualification × ICT	-0.139***	0.0831	-0.796	-0.300	-0.556	-0.299	-1.192
	(0.0291)	(0.0872)	(0.574)	(0.265)	(0.354)	(0.544)	(1.166)
No Qualification × ICT	-0.186***	0.243*	0.151	-0.505	0.354	-0.148	2.419
	(0.0401)	(0.106)	(0.470)	(0.274)	(0.393)	(0.568)	(1.355)
Age	0.362***	-0.358***	-1.117**	0.382	0.0283	-1.079**	0.0959
	(0.0273)	(0.101)	(0.394)	(0.227)	(0.275)	(0.415)	(0.574)
Age × Age	-0.00316***	0.00152*	-0.00843**	-0.00328*	-0.00360*	0.000741	0.00631
	(0.000215)	(0.000607)	(0.00266)	(0.00165)	(0.00183)	(0.00320)	(0.00480)
Individual*Industry FE	X	X	X	X	X	X	X
Education Level FE	X	X	X	X	X	X	X
Year FE	X	X	X	X	X	X	X
Region FE	X	X	X	X	X	X	X
Observations	174734	210867	103378	215711	215711	215711	53899

Note: All columns use the main specification. Column (1) reports the results for hourly wage, column (2) for the probability to become unemployed, column (3) for voter turnout, column (4) for vote for the Conservatives, column (5) for vote for Labour, column (6) for vote for the incumbent and column (7) for vote for UKIP. Except for the the wage variable, all results in percentage points. Standard error reported in parenthesis are clustered at the industry-year level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

4.9 Other political outcomes

The following tables report the full regression results of additional analyses examining if digitalization affects support for the Liberal Democratic Party and UKIP.

We do not find a change in the support for the Liberal Democratic Party among workers who experience digitalization. The Liberal Democratic Party is a centrist party that includes both classical economic liberals as well as social-democrats. The two main wings have varying strengths across constituencies and over time. One possible interpretation of this finding is that these different factions within the party cancel each other out. It is furthermore noteworthy that it seems that Libdem could not capitalize from an incumbency advantage.

As already graphically presented in the main text, we find some tentative evidence for increased UKIP support among the lowest qualified respondents in our sample, which would be consistent with the possibility that digitalization makes losers more likely to support anti-establishment parties, in this case from the radical right. Among workers with no formal qualification, an increase in ICT intensity produces a substantively large increase in the likelihood to support UKIP. However, the point estimates are never significant. These results have to be interpreted with caution since they are based on a short period of time and small sample. The option to report support for the UKIP is only provided since 2013 and the no qualification group only constitutes 4% of responses in those years.

Table 12: Support for the Liberal Democratic Party

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	-0.0673	-1.557**	-0.00233	-0.0643	-0.106	-0.0124	-0.0670	-0.700	0.153**
	(0.145)	(0.595)	(0.00220)	(0.146)	(0.228)	(0.173)	(0.0788)	(0.430)	(0.0550)
Other higher degree × ICT	-0.0405	-0.963	-0.00224	-0.0242	0.0625	-0.158	-0.136	-0.161	0.0797
	(0.205)	(0.662)	(0.00265)	(0.204)	(0.275)	(0.226)	(0.0932)	(0.420)	(0.0576)
A-Level etc × ICT	0.180	0.194	-0.000955	0.213	0.188	0.301*	-0.0738	0.209	0.189***
	(0.129)	(0.684)	(0.00201)	(0.130)	(0.185)	(0.136)	(0.0878)	(0.329)	(0.0546)
GCSE etc × ICT	0.0770	-0.860	-0.00326	0.0952	0.136	0.135	0.0452	-0.131	0.277***
	(0.133)	(0.440)	(0.00230)	(0.134)	(0.201)	(0.122)	(0.0849)	(0.521)	(0.0592)
Other Qualification × ICT	0.217	-0.656	0.00266	0.242	0.269	0.314	-0.0984	0.0893	0.183*
	(0.190)	(0.640)	(0.00427)	(0.188)	(0.238)	(0.253)	(0.145)	(0.382)	(0.0725)
No Qualification × ICT	0.260	0.0747	0.00213	0.196	0.345	0.0792	-0.0137	0.216	0.0865
	(0.243)	(0.826)	(0.00246)	(0.238)	(0.325)	(0.301)	(0.119)	(0.291)	(0.0756)
Age	0.279	0.268	0.126	0.127	0.301	0.431*	0.0561	0.133	-0.250***
	(0.200)	(0.205)	(0.202)	(0.202)	(0.202)	(0.212)	(0.187)	(0.465)	(0.0349)
Age × Age	0.000720	0.000931	0.000976	0.000975	0.000656	0.000146	0.00148	-0.00403	0.00378***
	(0.00136)	(0.00142)	(0.00136)	(0.00136)	(0.00137)	(0.00151)	(0.00121)	(0.00298)	(0.000429)
Imports								0.00556	
								(0.0235)	
Female									0.919***
									(0.142)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	221033	215766	221033	221033	218050	189117	219768	34592	221033

Note: Probability to report to support the Liberal Democratic Party in percentage point. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

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Table 13: Support for UKIP (only asked since 2013)

	(1) Main	(2) IV	(3) Placebo	(4) Region*Year FE	(5) Excl. outliers	(6) Lead	(7) ID FE	(8) Trade	(9) Cross Sect
Degree × ICT	-0.435	-1.969	0.0130	-0.351	-0.237	0.331	-0.283	-0.966	0.0852
	(0.341)	(1.545)	(0.0148)	(0.339)	(0.544)	(0.412)	(0.343)	(0.848)	(0.342)
Other higher degree × ICT	-0.338	-1.679	0.00999	-0.300	-0.797	-1.133*	-0.194	-0.612	0.179
	(1.034)	(2.250)	(0.0151)	(1.023)	(0.706)	(0.570)	(0.464)	(2.074)	(0.347)
A-Level etc × ICT	-0.888	-2.569	0.00616	-0.808	-0.711	0.198	-0.391	-3.748	0.130
	(0.459)	(1.870)	(0.0137)	(0.459)	(0.565)	(0.359)	(0.348)	(2.246)	(0.346)
GCSE etc × ICT	0.0324	-1.181	-0.0101	-0.0168	-0.369	0.649	-0.348	3.090	0.243
	(0.642)	(1.857)	(0.0176)	(0.641)	(0.703)	(0.400)	(0.398)	(2.047)	(0.352)
Other Qualification × ICT	-1.191	-0.0164	-0.0269	-1.201	-1.356	-1.696	-0.290	6.237	0.237
	(1.162)	(2.562)	(0.0255)	(1.163)	(1.267)	(1.050)	(0.503)	(3.773)	(0.363)
No Qualification × ICT	2.422	5.436	0.0707	2.482	2.319	1.137	0.00711	22.43*	0.309
	(1.354)	(3.376)	(0.0461)	(1.356)	(1.404)	(0.729)	(0.612)	(10.25)	(0.374)
Age	0.0727	0.0949	0.0298	0.0478	-0.0332	-0.595	-0.146	2.741	-0.00367
	(0.572)	(0.574)	(0.575)	(0.573)	(0.574)	(0.474)	(0.555)	(2.025)	(0.0529)
Age × Age	0.00648	0.00627	0.00669	0.00648	0.00765	0.00758*	0.00851	-0.0207	0.000821
	(0.00479)	(0.00483)	(0.00481)	(0.00479)	(0.00479)	(0.00376)	(0.00455)	(0.0165)	(0.000655)
Imports								0.00335	
								(0.0711)	
Female									-1.428***
									(0.193)
Individual*Industry FE	X	X	X	X	X	X		X	
Education Level FE	X	X	X	X	X	X	X	X	X
Year FE	X	X	X		X	X	X	X	X
Region FE	X	X	X		X	X	X	X	X
Year*Region FE				X					
Individual FE							X		
Industry FE							X		X
Observations	54147	53005	54147	54147	53505	60122	54019	7108	54147

Note: Probability to report to support the United Kingdom Independence Party in percentage point. Column (1) is our main specification with industry-spell fixed-effects. In column (2), we instrument ICT with data from the USA. Column (3) uses non-ICT capital per worker as main regressor. Column (4) is equivalent to the main specification with adding region by year fixed-effects. In column (5) we exclude the most digitalized industries. Column (6) uses the lead of the dependent variable. Column (7) uses individual fixed-effects and industry fixed effects. Column (8) includes a control for trade. Column (9) is a cross sectional analysis without individual fixed effects. Standard error reported in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

5 Mechanisms

5.1 Operationalization and Data Availability

The three dependent variables of the mechanism section are operationalized as follows:

- Satisfaction with Life: Likert scale of:
  - "Satisfaction with Life overall" (lfsato, sclfsato), 1=completely dissatisfied, 7=completely satisfied. Linearly imputed within individual if missing between two non-missing values.
- Supports Government Intervention: Principal component analysis (PCA) of:
  - "Private enterprise solves economic probs" (opsocc), 1=strongly agree, 5=strongly disagree. Linearly imputed within individual if missing between two non-missing values.
  - "Government has obligation to provide jobs" (opsoce), 1=strongly disagree, 5=strongly agree (recoded). Linearly imputed within individual if missing between two non-missing values.
- Social Progressiveness: Principal component analysis (PCA) of:
  - "Pre-school child suffers if mother works" (scopfama), 1=strongly agree, 5=strongly disagree. Linearly imputed within individual if missing between two non-missing values.
  - "Family suffers if mother works full-time" (scopfamb), 1=strongly agree, 5=strongly disagree. Linearly imputed within individual if missing between two non-missing values.
  - "Husband and wife should contribute to hh income" (scopfamd), 1=strongly disagree, 5=strongly agree (recoded). Linearly imputed within individual if missing between two non-missing values.

The underlying survey items are only included infrequently in BHPS/UKHLS. Table 14 provides an overview of their availability. Talbe 15 gives basic descriptive statistics.

Table 14: Availability of Survey Items over Time (N obs)

Year	Satisfaction	Gov Intervention	Progressiveness
1997	5896	5847	5835
1998	5859	5057	104
1999	6206	4574	5972
2000	7246	5715	1821
2001	7705	6960	7385
2002	7781	5750	1440
2003	8908	5957	7652
2004	8298	7807	355
2005	8495	6738	7680
2006	8163	6477	207
2007	7935	7196	7184
2008	7663	273	233
2009	11425	0	0
2010	24302	0	13480
2011	24040	0	8665
2012	22388	0	12626
2013	21525	0	7993
2014	20407	0	556
2015	18814	0	0
2016	19262	0	0
2017	8213	0	0
2018	909	0	0

Table 15: Mechanism Items: Descriptives

	count	mean	sd	min	max
Satisfaction	261’440	5.2	1.285	1	7
Government Intervention	68’351	0	1.081	-3.356	3.153
Progressiveness	89’188	0	1.323	-3.491	2.713

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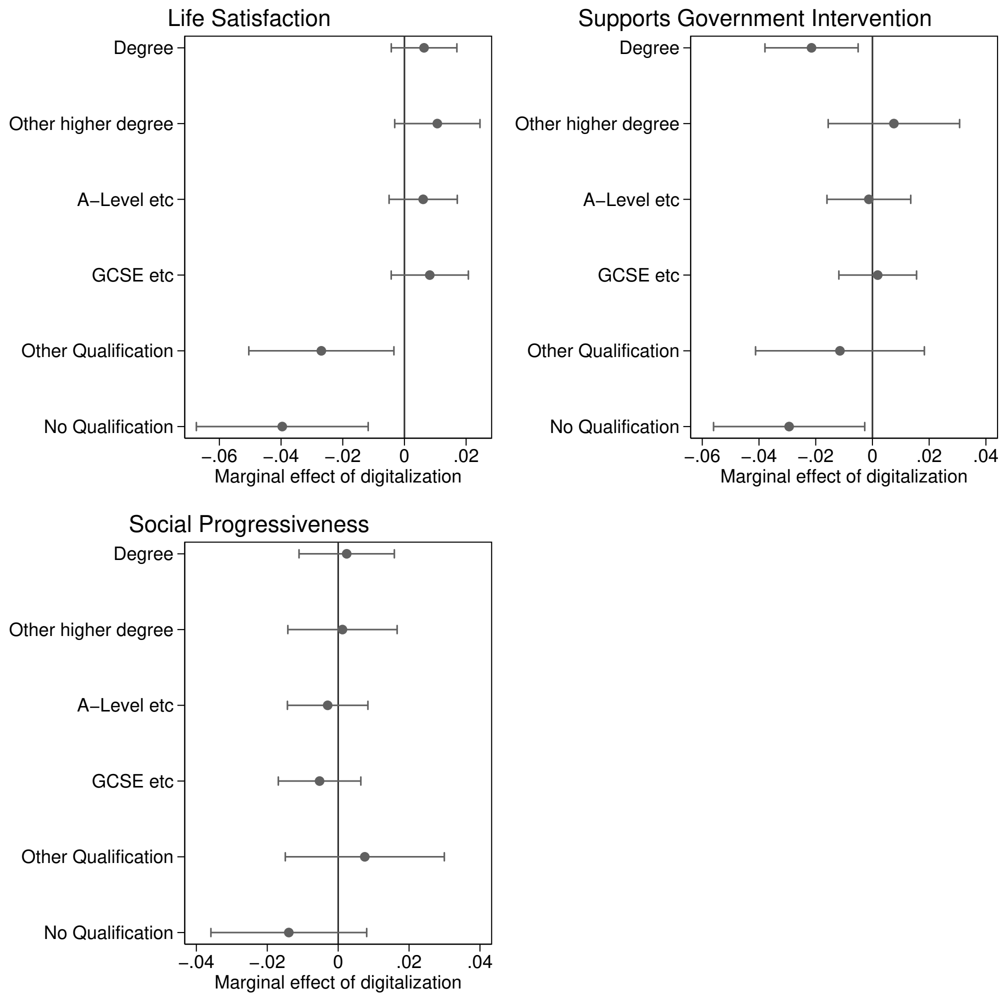
5.2 Results

Figure 7 presents the results of the analyses about mechanisms, which are discussed in the main text.

Figure 7: Effect of digitalization on satisfaction and attitudes



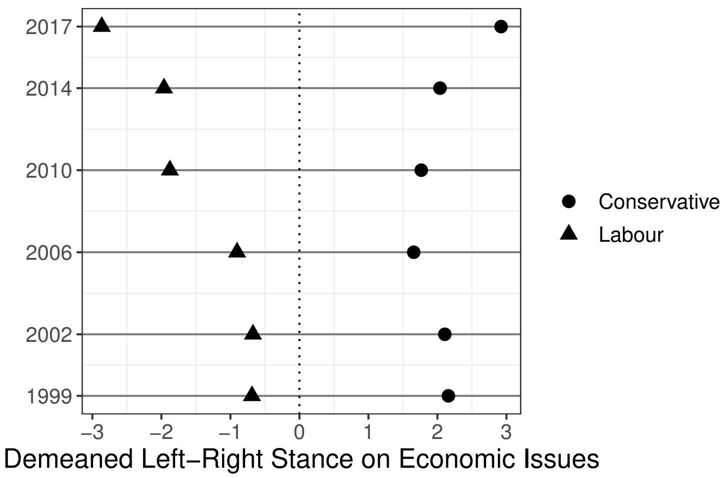
Note: Results show marginal effect of one unit increase in digitalization (1000 GBP in ICT capital/worker) on specified dependent variable, industry-spell fixed-effects specification.

6 Additional Description of the UK Political Context

6.1 Positions of the parties over time

We use Chapel Hill Expert Survey to back the claim in the main text that the Labor Party has been more pro-redistribution throughout the time period studied.

Figure 8: Position on Redistributive Issues



Source: Chapel Hill Expert Survey. Values of economic left-right position (lrecon) demeaned by year across all available party positions. Party positions weighted by vote share.

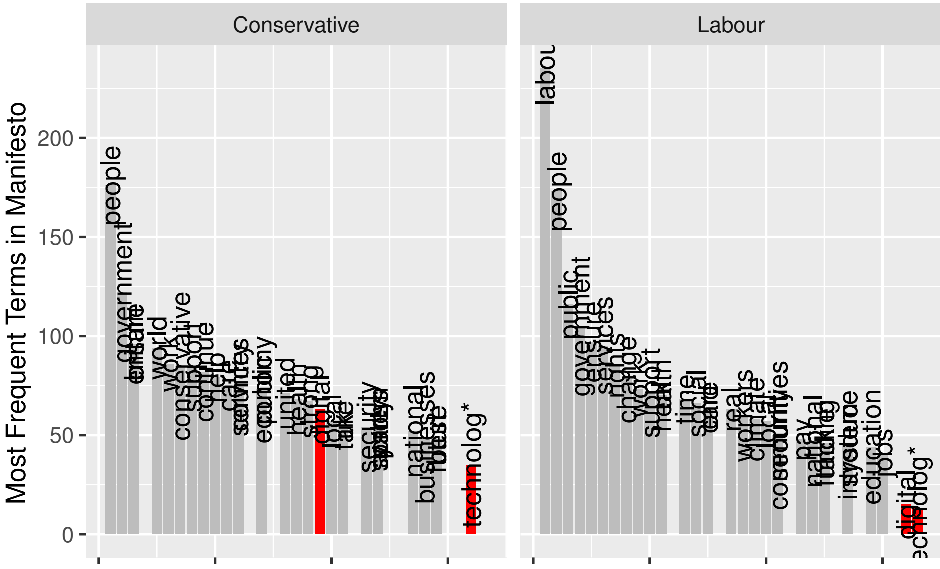
6.2 Party Manifestos

In order to get a more precise idea of potential supply-side effects related to the framing of the digitalization debate, we undertook an original analysis of the two large parties' most recent manifestos. We studied the content of the Conservative and Unionist Party Manifesto 2017 ("FORWARD, TOGETHER. Our Plan for a Stronger Britain and a Prosperous Future", 88 pages, available online [access date: November 22, 2019]) and the Labour Party Manifesto 2019 ("It's time for real change", 107 pages, available online [access date: November 22, 2019]). The Conservative 2019 Manifesto was not yet available at the time of writing. If anything, we would expect the less recent manifesto to result in a downward bias of attention to digitalization compared to the Labour Party.

We examine if the two parties differed in the extent to which they discuss digitalization and technology in their manifestos. A simple key word analysis demonstrates that the Conservative Party speaks more about these issues than the Labour party. In general, attention to the topic is surprisingly limited in both manifestos, which might reflect the difficulty to claim ownership of a newly emerging issue (König and

Wenzelburger, 2018). Still, while apparently not being a priority, the relevant concepts at least appear among the Conservative's top-30 terms. This is not the case for the Labour manifesto, which has been released very recently. Figure 9 gives a broad overview and provides a comparison between the two parties.

Figure 9: Digitalization: ICT capital stock per employee, by industry



We next looked at the relevant keywords in context to get a better sense of the way the Conservative Party tried to frame the debate. A simple overview in Table 16 suggests that they address the issue in an almost exclusively positive sense, in which digitalization benefits businesses and the economy in general. Digital technology, according to the Conservative Party, promises prosperity and security. Another frequent feature is the use of new technology to increase government efficiency and public services, e.g. related to NHS. A final important aspect is investment in skills to seize the opportunities provided by new technologies.

To summarize, it can be said (a) that digitalization has not featured very prominently in the two main parties' manifesto in absolute terms, (b) that the Conservative Party was considerably more attentive to the issue in relative terms, and (c) that it discussed almost exclusively the beneficial aspects of new technologies. We conclude that our simple supply-side analysis supports the idea that the Conservative Party is a reasonable political choice for ordinary winners of digitalization throughout the whole period.

Table 16: Topfeatures related to Digitalization in Conservative Manifesto

	topfeatures(kwic_cons, 30)
technology	10.0
economy	9.0
services	8.0
digital	8.0
age	8.0
prosperity	7.0
security	6.0
government	6.0
help	6.0
use	6.0
charter	6.0
new	5.0
companies	5.0
businesses	5.0
infrastructure	5.0
right	4.0
skills	4.0
public	4.0
creative	3.0
data	3.0
strategy	3.0
ensure	3.0
provide	3.0
online	3.0
support	3.0
access	3.0
also	3.0
need	3.0
people	2.0
working	2.0

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