Not so Disruptive after All: How Workplace Digitalization Affects Political Preferences

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Neither Left-Behind nor Superstar: Ordinary Winners of Digitalization at the Ballot Box*

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Abstract

The nascent literature on the political consequences of technological change studies either left-behind voters or successful technology entrepreneurs ("superstars"). However, it neglects the large share of skilled workers who benefit from limited but steady economic improvements in the knowledge economy. This paper studies how workplace digitalization affects political preferences among the entire active labor force by combining individual-level panel data from the United Kingdom with industry-level data on ICT capital stocks between 1997-2017. We first demonstrate that digitalization was economically beneficial for workers with middle and high levels of education. We then show that growth in digitalization increased support for the Conservative Party, the incumbent party, and voter turnout among beneficiaries of economic change. Our results hold in an instrumental variable analysis and multiple robustness checks. While digitalization undoubtedly produces losers (along with some superstars), ordinary winners of digitalization are an important stabilizing force content with the political status quo.

Keywords: Technological Change, Digitalization, Political Preferences, Voters

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Introduction

The latest wave of technological change is profoundly reshaping labor markets. The spread of computers, smart software, robots and, increasingly, artificial intelligence has sparked debates about the future of work and potential repercussions in the political arena. While pessimistic voices emphasize the potential of new technologies to replace human labor and cause political upheaval, tech optimists point to a long history of misguided fears of technological unemployment.[1]

A rich literature in labor economics studies the large but unequally distributed benefits of recent technological innovation. Routine-biased technological change has mostly substituted tasks that can be accomplished by following explicit rules and thus reduces the number of routine jobs in the lower middle of the income distribution. At the same time, digital technologies complement many workers concerned with more complex tasks, increase their productivity, and create high-quality jobs (Autor, Levy and Murnane, 2003; Acemoglu and Restrepo, 2019). The resulting process of "upskilling" in an increasingly digital world of work is a central feature of the emergence of the knowledge economy (Iversen and Soskice, 2019; Hope and Martelli, 2019; Boix, 2019*a*).

Does this crucial economic transformation affect the political preferences of workers? Despite the evident economic benefits of digitalization, most media accounts as well as the nascent scholarly literature dealing with the political consequences of technological change have primarily been concerned with its downsides and risks, and have focused on groups left behind by this process (Frey, Berger and Chen, 2018; Im et al., 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020). Another highly visible group that has received considerable attention are exceptionally successful and politically influential technology entrepreneurs (Broockman, Ferenstein and Malhotra, 2019). Even though both "left-behinds" and "superstars" are important constituencies, the majority of workers does not belong to either group.

In this article, we seek to provide a more encompassing understanding of the political consequences of digitalization by studying how increases in ICT capital intensity in an industry affects the political preferences of workers. Our empirical analysis uses longitudinal data from the United Kingdom that encompasses all individuals who remain active in a changing labor market. The core contribution of this paper is to document that digitalization generates a large group of "ordinary winners", i.e. skilled workers who have the cognitive abilities to productively use new technologies at the workplace, and to

[1] A note on terminology: We use the term digitalization to analytically distinguish from the more generic term of technological change.

show that the political preferences of such workers who benefit economically from this development change in a stabilizing pro-system direction.

In addition, our innovative empirical approach improves on two weaknesses of existing work about the political consequences of technological change. A first concern is measurement. The aforementioned studies rely either on indirect indicators of exposure to digitalization based on the prevalence of routine tasks in an occupation or on a more direct measure of exposure to robotization. Indicators of routine task intensity (RTI) capture the task content of an occupation at a certain point in time rather than over-time variation in technology exposure. Hence, RTI has difficulty isolating a "technology effect" from other relevant occupational characteristics. The prevalence of industrial robots, on the other hand, certainly represents a key source of pressure for particular industries, e.g. automotive production. But its consequences are of more limited relevance in the many non-manufacturing domains of the economy. We measure digitalization differently, namely as industry-specific capital stocks of information and communication technology (ICT). Importantly, ICT capital is a time-varying measure of investment in digital technology that applies to all industries. As such, it is well-suited for an analysis of the economic and political implications of digitalization among the entire labor force.

A second limitation of existing work concerns identification. Pioneering publications have relied on cross-sectional or regional data. We merge our indicator of digitalization to rich individual-level panel data from the United Kingdom and fit a series of fixed effects models to provide plausibly causal estimates of the effects of digitalization on political preferences. Panel data substantially reduce concern about omitted variables by focusing on within-individual change, which rules out that the results are driven by selection of individuals to industries or individual- and industry-level time-invariant variables. In addition, we support the causal interpretation of our findings through an instrumental variable approach and a series of robustness checks.

The empirical analysis demonstrates that a large share of the population indeed benefits economically from investment in new technology and that this economic process has political consequences. In contrast to accounts that highlight the disruptive potential of technological change among the "left behind", we show that exposure to digitalization increases wages for a majority of workers, a process that does not come at the cost of substantially higher unemployment. These economic benefits in turn entrench support for the political status quo: Digitalization leads to increased (a) support for the Conservative party, (b) support for the incumbent, and (c) voter turnout among ordinary winners of digitalization.

Our finding that digitalization is economically beneficial for a majority of workers and that these workers become more likely to support center-right mainstream and incumbent parties does not preclude that certain subgroups of society suffer in absolute or relative terms and might increasingly support anti-system forces. Indeed, we do find some evidence that unskilled workers, who are most susceptible to the downsides of automation, are increasingly drawn to right-wing populists when their industry digitalizes. Still, our paper shows that technological change does not only shape politics by creating a reservoir of dissatisfied losers who find the political remedies offered by populist or anti-establishment parties appealing, but it also increases support for the establishment and the democratic status quo among the large group of beneficiaries. Rather than creating dissatisfaction across the board, digitalization generates political divergence between a majority of beneficiaries and a minority of non-beneficiaries and thus presumably contributes to increasing political polarization.

To the best of our knowledge, this is the first paper that produces well identified individual-level effects of workplace digitalization on political outcomes using panel data. We contribute to the political economy literature on current political realignments and populist upheaval (Boix, 2019*b*; Iversen and Soskice, 2019; Rodden, 2019). These important accounts point to the "knowledge economy" or the "fourth industrial revolution" as the main economic force underlying changing voting patterns, party realignments, and political geography, but they do not attempt to directly measure technological change and have not examined if the introduction of digital technology modifies workers' political preferences.

We also contribute to the growing literature about how economic shocks and changes in labor market outcomes alter political preferences and vote choices (see Margalit, 2019). These studies typically focus on intense negative changes in economic standing, such as unemployment experiences or large income drops. The question of whether positive changes in the workplace situation affect political behavior has received less attention. The few well-identified studies focus mostly on large, exogenous shocks such as winning the lottery (e.g. Doherty, Gerber and Green, 2006). We extend this literature by focusing on a particular source of changes in the workplace, digitalization, which produces smaller but more continuous economic effects on workers' economic fortunes than shocks studied previously.

Digitalization: Economic Outcomes and Political Responses

The introduction of new technology at the workplace is a source of continuous change in workers' situation in advanced capitalist democracies. In a nutshell, our argument has three steps: Digitalization has important distributive consequences and impacts wages and unemployment risk. Therefore, digitalization affects voters' attitudes and economic preferences. This in turn links digitalization to voting conservative, voting for the incumbent, or voting for mainstream parties more generally rather than supporting populists or abstaining. Crucially, all of this is moderated by education because the more highly educated benefit more from digitalization while the less educated suffer wage reductions and face more difficult employment prospects in the digital age. Digitalization hence generates political divergence between a majority of beneficiaries and a minority of non-beneficiaries and contributes to increasing political polarization.

The (many) winners and (fewer) losers of digitalization

Recent theoretical work contends that the effects of technological change on wages and employment depend on the outcome of two countervailing forces (Acemoglu and Restrepo, 2019): a displacement effect as machines start to perform tasks previously done by humans and a productivity effect, as they complement workers and free up time spent on dull tasks. The net effect of these two forces on wages and employment is a priori uncertain but empirical estimates suggest that the productivity effect has dominated in past centuries (Mokyr, Vickers and Ziebarth, 2015). Technology, along with well-designed complementary institutions, is the most important cause of the unrivaled growth in output and living standards since the Industrial Revolution. Positive net effects also hold during the last wave of technological innovation, which is characterized by the extension of information and communication technologies (ICT). Our first expectation is that a majority of workers economically benefit from the introduction of new digital technologies.

A related, less optimistic expectation is that positive net effects go hand in hand with significant heterogeneity. While digitalization has increased the demand for highly educated workers, it has substituted for less skilled work and those in routine occupations (e.g. Autor, Levy and Murnane, 2003; Goldin and Katz, 2009). At the aggregate level, these countervailing effects have produced a pattern of job polarization (Goos, Manning and Salomons, 2014). How the well-documented reduction in jobs in mid-paying occupations translates into individual economic fortunes is less clear and represents one of the questions we set to explore. A decline in semi-skilled jobs does not necessarily imply that individual semi-skilled workers suffer downgrading over time. The observed aggregate reductions in mid-paying jobs might be absorbed by retirement without replacement or by exit to other, potentially higher-paying, jobs (Dauth et al., 2017; Cortes, 2016; Kurer and Gallego, 2019). In short, we expect that the introduction of new digital technologies in the workplace has positive economic consequences for a majority of workers. However, these benefits are unevenly distributed and mostly accrue to workers who possess the cognitive abilities to use new technologies productively.

Political implications of digitalization

To derive expectations about political ramifications, we draw on theoretical accounts that view individual's economic self-interest as an important determinant of vote choice. We consider economic channels as a key mechanism linking workplace digitalization to changing political behavior, but do not rule out the existence of non-economic psychological channels. In contrast to most existing work, we do not narrow our focus on workers left behind by technological change. Because technological change might have positive net effects, we are just as interested in the theoretical implications for ordinary winners of digitalization.

Drawing on the small existing literature on political ramifications of digitalization as well as on the broader literature on the impact of economic changes, we discuss four possible effects. The first possibility is that workers at risk of displacement due to automation demand more protection and support for redistribution (Thewissen and Rueda, 2017), which should push them to vote for parties that defend economically left-wing policies. The mechanism is consistent with standard models of voting based on preferences for economic platforms, which depict political competition as a conflict about redistributive issues, where individual material circumstances and economic risk are a main driver of policy preferences and, ultimately, party support (e.g. Iversen and Soskice, 2006; Margalit, 2013; Rehm, Hacker and Schlesinger, 2012). In the case of the UK, this argument implies that workers who are harmed economically by digitalization may become more supportive of the Labour Party while workers who benefit become more likely to support to the Conservative Party.[2]

[2]Although Labour's absolute position on redistributive issues has varied over time, expert survey data on the two major parties' economic left-right position leaves no doubt about the two parties' relative position, even during the Blair era (see Figure SI0.8 in the SI).

A second possibility is that workers who are economically affected by digitalization respond by voting for or against the incumbent. Frey, Berger and Chen (2018) find that US counties with a higher exposure to industrial robots experienced larger shifts in vote shares in favor of the Republican Party between 2012 and 2016. They interpret this finding as anti-incumbent voting, an interpretation that is congruent with research about the political consequences of other structural transformations such as off-shoring and trade with China (Margalit, 2011; Jensen, Quinn and Weymouth, 2017; Autor et al., 2016). The basic mechanism in this case is economic voting: negative changes in economic prospects should generate dissatisfaction with the status quo and motivate workers to support parties in the opposition. Conversely, improvements in workers' economic situation due to digitalization should increase satisfaction and increase the likelihood of supporting the incumbent.

A third possibility, and the one that has received most attention so far, is that workers who are threatened in their jobs or lose out economically from being in digitalizing work environments become more likely to vote for anti-system, radical right-wing parties (Im et al., 2019; Kurer and Palier, 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020). The key mechanism in this case is related to changing social hierarchies and the lacking trust of the disadvantaged in the political system to improve conditions and provide the left-behind with the recognition they seek. This option might have limited applicability in contexts with majoritarian electoral systems where fringe parties are not electorally viable in many constituencies. Still, we examine this third possibility by studying if workers who lose out economically from digitalization become more likely to support the UKIP (in the years this party is included in the study), while workers who benefit economically do not.

A fourth conceivable way in which technological change affects electoral outcomes is via turnout, i.e. the possibility that digitalization affects the probability to turn out in elections. One possible channel is related to changes in the resources available to participate in politics. In particular, a drop in resources can lead to "political withdrawal" as citizens concentrate on solving more pressing problems (Rosenstone, 1982). Alternatively, psychological changes, i.e. the realization that tasks previously performed by humans can be carried out by machines, might undermine feelings of self-efficacy and self-esteem, which are important precursors of political engagement (Marx and Nguyen, 2016). The reverse applies to winners of digitalization.

All four possibilities are reasonable ways in which digitalization can affect voting behavior. Previous research in political science about the impact of changes in workers' economic situation provides little guidance about which option is most plausible. In fact, in a recent review of the literature, Margalit (2019) compiles abundant evidence that negative economic shocks, such as becoming unemployed or experiencing income drops, can produce different political effects, including anti-incumbent voting, support for radical parties, support for the left, or a reduction in voter turnout, and concludes that "research to date offers very limited insight on the conditions that lead to one such response over another" (2019, p. 279). For this reason, we examine all possibilities in our empirical analysis and attempt to examine distinct mechanisms, including attitudes about economic issues and overall satisfaction.

Note that the four possibilities apply even in the absence of public debate about the issue of digitalization and even if workers do not consciously relate changes in their workplace due to digitalization (which may affect them economically or psychologically) to their party choice.[3] For instance, voters may just rely on loose cues about general satisfaction to evaluate the performance of the incumbent. Our theoretical expectations could vary if parties more actively politicized the issue of digitalization. However, as in other Western European democracies (König and Wenzelburger, 2018), digitalization remains a marginal issue in UK party manifestos in spite of the pressure for policy change. An analysis of the most recent manifestos shows particularly little attention to digitalization and new technology in the Labour manifesto. The Conservatives talk somewhat more about this topic and, interestingly, do so in an almost exclusively positive tone highlighting business opportunities, prosperity and security (details provided in the SI). If anything, we would hence expect that their way to address the issue is particularly appealing to winners of digitalization.

Data and descriptive overview

Our empirical analyses focus on the case of the UK, an established democracy at the frontier of technological innovation for which rich longitudinal micro-level data are available.

[3] One might reach different conclusions when studying more specific and fine-grained policy preferences instead of general preferences in favor of a center-left vs. a center-right party. For example, Barber, Beramendi and Wibbels (2013) have demonstrated substantial informational barriers when voters are asked to distinguish between the redistributive and insurance elements of public policy.

Industry level measure of digitalization

To measure digitalization, we follow Michaels, Natraj and Van Reenen (2014), who use yearly changes in ICT capital stocks within industries (see also Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). This is our main explanatory variable. We use the September 2017 release of the EU-KLEMS dataset (Jaeger, 2016), which contains yearly measures of output, input and productivity for 40 industries in a wide range of countries, including the UK, and covers the period 1997 to 2015. The data is compiled using information from the national statistical offices and then harmonized to ensure comparability. Most importantly for our purposes, the database provides a breakdown of capital into ICT and non-ICT assets (O'Mahony and Timmer, 2009). This allows for the creation of time-varying, industry-specific indicators of digitalization based on ICT stocks. We extend the existing time-series until 2017 on the basis of cross-classified Eurostat data on fixed assets by industry and asset (stocks), indexed by 2015 EU-KLEMS values.

Our measure of digitalization is constructed as follows:

$$\mathrm{D}_{j,t} = \frac{(\text{ICT capital stock in thousand GBP}_{j,t})}{(\text{Employees}_{j,t})}$$

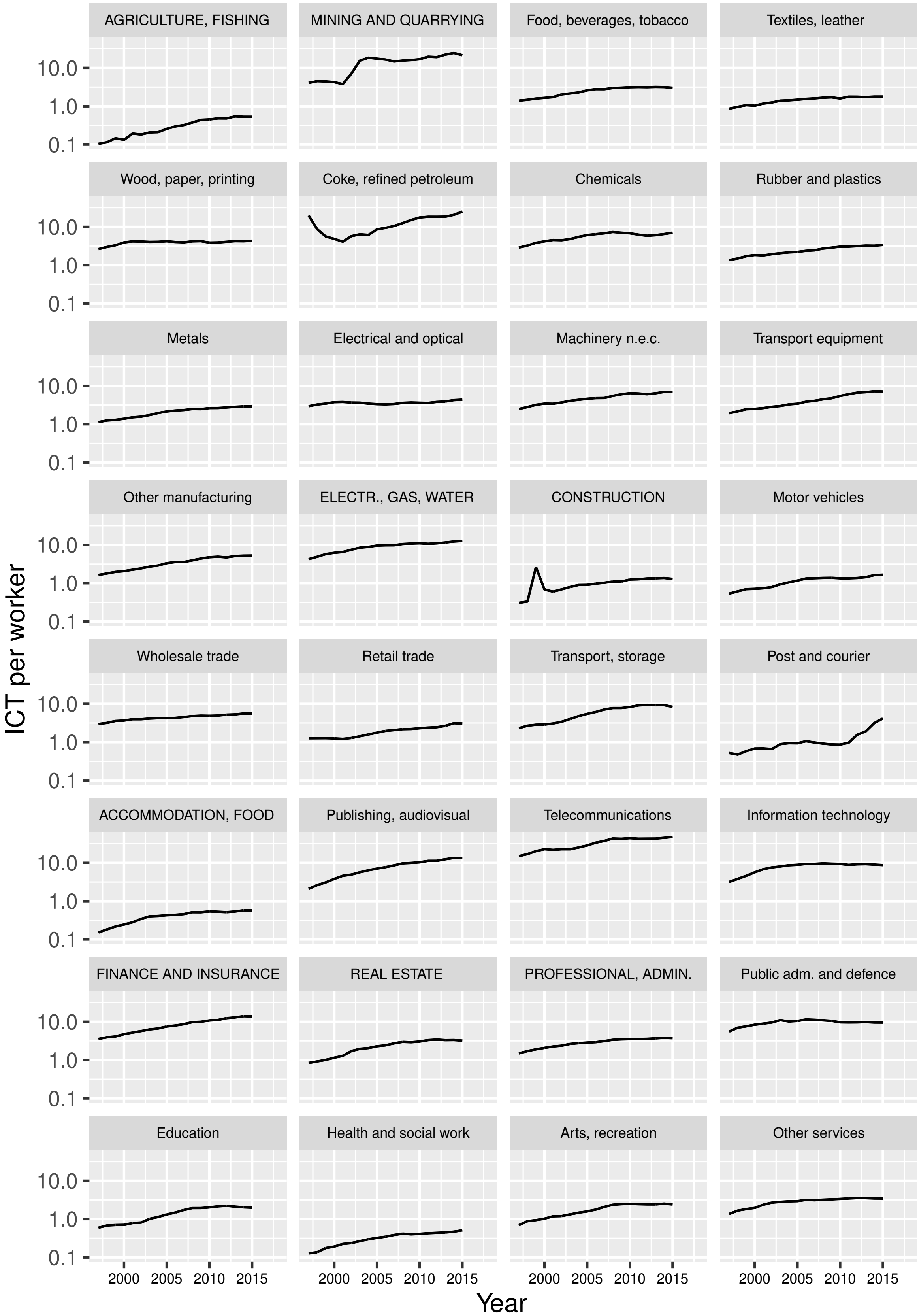
Where ICT capital stock$_{j,t}$ is the sum of the fixed capital stocks in computing equipment, communications equipment, computer software and databases in industry *j* in year *t*, at constant 2010 prices, and is normalized by the number of employees in that industry.[4]

Figure 1 plots the evolution of our indicator of digitalization over time for the industries provided by EU KLEMS.[5] Some industries are disaggregated only at the 1-digit level (e.g. Agriculture, forestry and fishing), while for other industries EU KLEMS also breaks down the data at the more fine-grained 2-digit level (e.g. manufacturing is disaggregated into 11 categories such as "food products, beverages and tobacco").

[4]Productivity-enhancing and potentially labor-replacing investments can in principle affect our measure in two ways. First, they increase the numerator (the ICT capital stock) and second, they can reduce the denominator if labor-saving technologies are implemented and reduce the number of employees in the industry. This is a manifestation of the two-fold consequences of digitalization: It can be beneficial for workers by increasing productivity or threatening if it reduces labor demand. Our measure hence captures ICT intensity relative to labor in an industry, rather than ICT intensity in an absolute sense.

[5]EU KLEMS data is disaggregated by 35 industries based on the industry standard classification system used in the European Union (NACE rev1). For 3 industries, ICT data is missing or has only zero values which reduces our sample to 32. NACE codes are consistent with UK SIC codes provided in the BHPS, which allows for a comprehensive merge of the two datasets. The scale of the y axis is logged to facilitate visualization, but the analyses use the original variable, operationalized as discussed above.

Figure 1: Digitalization: ICT capital stock per employee, by industry



Note: Digitalization measured as yearly ICT capital stock per worker for the industries provided by EU KLEMS. Industries at the 1-digit level are written in capital letters, while industries at the 2-digit level are in lower case letters. The y-axis has a logarithmic scale to facilitate visualization.

As expected, we see a general increase in the importance of digital technologies over time. The levels of ICT intensity also vary across industries in a sensible way (e.g. they are highest for telecommunications, or finance and insurance, as we would expect), adding to our confidence that the measure is valid. If anything, the trend shown understates the true degree of digitalization as ICT prices fell over time.

An important difference between our measure and the more widely used measure of robotization (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020; Anelli, Colantone and Stanig, 2019; Frey, Berger and Chen, 2018) is that ICT investment has affected all sectors in recent decades, allowing us to study effects of digitalization across the entire labor force. ICT capital reshapes all sectors of the economy and only 40% of total investment takes place in manufacturing industries. By contrast, deployment of robots is more concentrated: In the UK in 2017, according to the International Federation of Robotics, more than 90% of the operational robots were used in manufacturing, by far the largest chunk of it in the automotive industry. Hence, while robotization certainly represents a key source of pressure on workers in certain manufacturing industries, our time-varying measure of technological change appears well-suited to study political repercussions in the broader population. ICT capital affects the entire active labor force and thus nicely complements other studies that focus on particularly disruptive but more concentrated technological innovation in specific sectors of the economy.

Individual-level survey data

We combine our measure of digitalization at the industry level with longitudinal data from the British Household Panel Study (BHPS) and the Understanding Society (UKHLS) survey. The BHPS is a longitudinal study that has interviewed about 10'000 individuals nested in 5'000 households drawn from a stratified random sample of the British population yearly from 1991 to 2008. In 2009 the BHPS was transformed and expanded into the Understanding Society (UKHLS) survey (see Buck and McFall, 2011). Every year participants are asked detailed questions about their economic situation, current and past employment, as well as a few political questions.

For each year (date of interview), we assign every worker the value of our measure of digitalization (ICT per worker) in his or her current industry. Because the latest release of EU KLEMS only covers the period since 1997, we exclude respondents surveyed between 1991 and 1996 from our study. We also exclude respondents aged 65 and older (who should be less affected by changes in the labor market) and respondents less than 18 year old. From the remaining sample, 71.3% can be linked to one of 32 industries (NACE rev. 2). We exclude extraterritorial organizations and households as employers as there is only very sparse information on ICT capital stocks. Our total final sample contains 287’352 observations for 61’071 unique individuals. Excluded from our sample are people not assigned to an industry (including students or the currently unemployed if no industry is reported), people who never enter the labor force, and people who have exited the labor force. Table SI0.1.1 provides detailed summary statistics of all variables used.

The dependent variables in our analyses are a set of indicators of the personal economic situation and political attitudes asked consistently over time by BHPS/UKHLS. We compute *hourly net wages* in constant 2010 prices using the variable usual net pay per month, which is derived by BHPS/UKHLS staff using answers to detailed income questions and imputed if this information is missing. This is normalized by hours worked. We exclude observations with less than half time employment (20 hours per week) from this analysis because we found that they contain considerable measurement error.

The *employment status* refers to the week when the respondent was interviewed. Due to the lack of information about unemployment spells between surveys, we can thus only look at the moment of the interview, which most likely provides a lower bound estimate. Since we are interested in the effect of digitalization on the probability to *become* unemployed, we focus on the effect of current digitalization on a worker’s probability to being unemployed at the time of the *next* interview.

Our measure of *voter turnout* is self-reported participation in the last general election, which is asked in all waves until 2008 and then in 2010, 2015, and 2017. We construct a *party support* variable using a series of questions asked every year on whether respondents consider themselves supporters of a party or (if they are not) if they feel closer to one political party than to the others.

To measure *support for the incumbent*, we code respondents as supporters of the incumbent party if they supported the Labour Party before the government change on May 7 2010 and the Conservative Party after it changed. The Liberal Democrats are coded as incumbents during their spell in the coalition government between May 2010 and May 2015.

Our key moderator variable, *education*, is coded in six categories: university degree (27% on average over the entire period); other higher degree (such as teaching or nursing, 12%), A-Level and other higher secondary qualifications (24%); General Certificate of Secondary Education, O-level and other lower secondary qualifications (22%); other qualifications (8%); and no formal qualifications (7%).

We concentrate on education rather than on task content, i.e. the distinction between routine vs non-routine occupations (Autor, Levy and Murnane, 2003), for theoretical and empirical reasons. Education is a generally stable individual characteristic, as relatively few people acquire higher educational credentials after finishing schooling in young adulthood. Intra-individual stability makes education more suited for our longitudinal analysis than routine task intensity (RTI), which is measured on the level of occupations and changes as workers switch between different jobs. RTI is hence a fluid and potentially endogenous characteristic giving rise to varied trajectories. More importantly, education should be correlated with individuals' unobserved cognitive skills and ability to learn and hence with their potential to adapt to and reap the benefits of the introduction of new digital technologies in the workplace. By contrast, it is unclear if the current RTI of a worker's job is informative about his or her ability to adapt to digitalization. In our empirical setting, which interacts an industry-level measure of digitalization with an individual trait capturing the capability to deal with this development, education is more informative about the ability to learn, retrain, and ultimately benefit from digitalization than routine task content of the current job. We support this claim with empirical evidence in section SI0.2 where we show that education is a stronger moderator than RTI in predicting whether workers are positively or negatively affected by digitalization in their industries.

Estimation and identification

Fixed-effects model

We use individual industry-spell fixed-effects models to estimate the effects of digitalization in a worker's industry on labor market and political outcomes. Our modelling strategy controls for all time-invariant individual and industry-level characteristics, and only uses over time variation in the level of digitalization within industries for workers who remain in the same industry for two or more periods to identify the effect of digitalization.

To test the expectation that the effects of digitalization on labor market and political outcomes are heterogeneous depending on workers' education level, we estimate separate slopes for the effect of digitalization in a worker's industry for workers with different education levels. Our baseline specification is:

$$Y_{ijt} = \sum_{s*=1}^{6} I_{[S_{it}=s*]}\delta_{s*} + \theta_0 \times D_{jt} + \sum_{s*=1}^{6} I_{[S_{it}=s*]}\theta_{s*} \times D_{jt} + \eta_{ij} + \mu_t + \boldsymbol{\gamma}'\mathbf{C}_{it} + \epsilon_{ijt} \qquad (1)$$

Where Y_{ijt} is the outcome of interest (economic or political) for individual i in industry j at time t. It is a function of six dummy variables $I_{[S_{it}=s*]}$, which take the value 1 if an individual has the corresponding education level and 0 otherwise. The coefficient vector $\boldsymbol{\delta}$ identifies separate intercepts for each education level.[6] We further add the time-varying measure of digitalization (ICT capital stock per worker) at the industry level D_{jt} described above and interact it with the education level dummy variables $I_{[S_{it}=s*]}$ to estimate a different slope for the effect of digitalization on economic and political outcomes for each education group. This is important as we argued that a worker's education level is a key moderator to understand the implications of being exposed to digitalization.

In our baseline specification, we include the term η_{ij}, a vector of individual by industry fixed effects (or industry-spell fixed effects) which captures all time-invariant variables that might affect labor market and political outcomes, self-selection of workers into specific workplaces, such as their gender, personality or family origin, as well as time-invariant industry-level characteristics. The industry-spell fixed effects include separate intercepts for the same individual in periods when he or she has worked in a different industry, which allows us to rule out that switchers to different industries are driving the results.[7] However, we also conduct extensive robustness checks to examine if our conclusions hold using alternative fixed effects specifications.

Furthermore, we include a year fixed effect μ_t. The fixed effect absorbs the impact of any contextual factors that are common to all individuals such as the growth of the economy or the performance of a given party. Hence, our analyses rely only on within-individual variation, controlling for circumstances that are common for all individuals. While the fixed effect capture most unobserved heterogeneity, we still add a vector $\mathbf{C}_{it}$ of time-varying individual-level controls. Here, we include age as a non-linear control because there is a sharp increase in the average values of most variables (such as hourly wages or voter turnout) during the 20s and 30s while their values level off later in life.

[6] For most individuals, the education level is constant in all waves of the study. In our fixed effect model, the coefficient vector $\boldsymbol{\delta}$ will only be identified by the few who upgrade their education level as education is otherwise absorbed by the individual fixed effect. Therefore, we do not focus on the direct effect of education when interpreting the results.

[7] This is important because differences in digitalization across industries are much larger than differences within industries from one year to another. Any changes occurring when workers move to a different industry (which may coincide with many other relevant changes besides digitalization) would dominate the more subtle effects of digitalization at a given workplace we are interested in.

To allow for the correlation of error terms of the same individual over time and when they work in different industries, we cluster the error term ϵ_{ijt} at the individual level. We report an alternative specification with standard errors clustered at the level of the variation of the treatment, that is on the industry-year level, in the SI.

Threats to identification

A key concern with our empirical approach is the possible endogeneity of our measure of digitalization. In particular, ICT capital stocks per worker in the UK could be influenced by governmental policies that also affect workers' economic and political outcomes, e.g. policies adopted to shelter some industries from competition or subsidies to accelerate or slow down the adoption of digital technologies in some industries in response to their political power. In return, workers employed in that industry could have a more favorable view of the party in power.

To address this concern, we follow recent work on the Chinese import shock (Autor, Dorn and Hanson, 2013) and instrument our measure of ICT capital stocks per worker in the UK (D_{jt}) with an analogous measure from the USA (D_{jt}^{USA}):

$$D_{j,t}^{USA} = \frac{(\text{ICT capital stock in the USA in thousand USD}_{\ j,t})}{(\text{Employees in the UK}_{j,t})}$$

In the second stage, $\tilde{D}_{jt}^{USA}$ represents digitalization in the UK instrumented with values from the USA:

$$Y_{ijt} = \sum_{s*=1}^{6} I_{[S_{it}=s*]}\delta_{s*} + \theta_0 \times \tilde{D}_{jt}^{USA} + \sum_{s*=1}^{6} I_{[S_{it}=s*]}\theta_{s*} \times \tilde{D}_{jt}^{USA} + \gamma \mathbf{C}_{it} + \eta_{ij} + \mu_t + \epsilon_{ijt} \quad (2)$$

The first stage of the IV analysis is strong (all F-statistics are larger than 75). This is to be expected given that the USA is clearly at the technological frontier and competition and profit maximization motivate industries in other countries to adopt these productivity-enhancing technologies once they exist. Digital technologies adopted in an industry in the US are likely to be adopted in the UK as well, perhaps with a time lag.

The exclusion restriction of our IV strategy is that changes in ICT capital stocks in the USA do not produce changes in the economic outcomes or political views of workers from the same industry living in the UK *if ICT stocks in the UK are held constant.* Channels other than technology diffusion are likely to impact workers in the UK too indirectly and too slowly to drive the effects we capture. Furthermore, given the unequal size of the countries, politics and economics in the UK are unlikely to affect the adoption of technology in the USA.

We address further concerns including the specificity of ICT investment as opposed to general investment, within-subject switching between industries, displacement effects of technology, regional effects, the impact of trade, and panel attrition, among others, in the robustness section.

Results

This section presents the marginal effect of a one-unit increase in digitalization (a 1000 GBP increase in the ICT capital stock per worker, which is equal to 1.4 standard deviations of within industry variation in ICT), for workers of different education levels. The complete regression tables are presented in the SI.

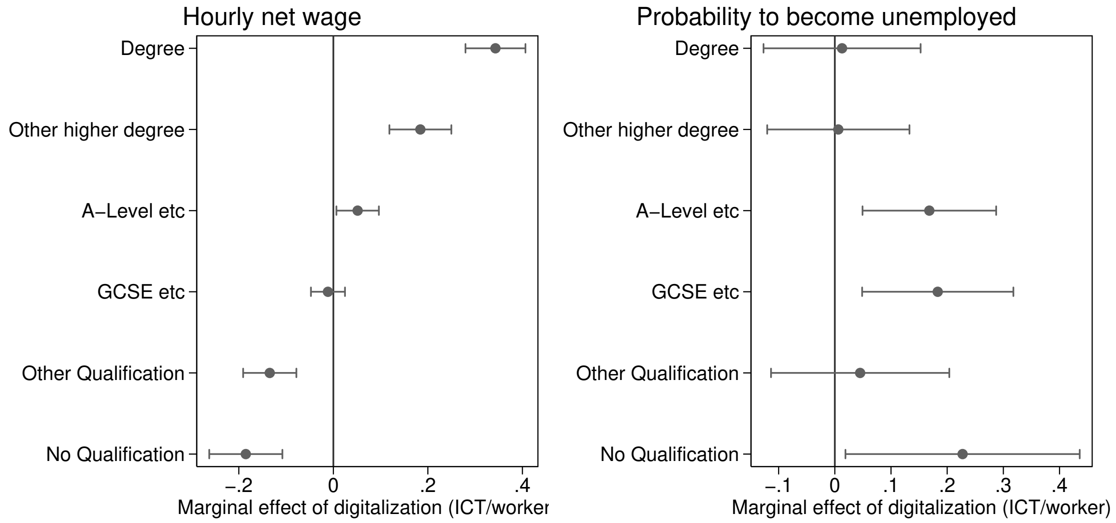
Digitalization and Labor Market Outcomes

The first part of our analysis tests our expectations about the distributive consequences of digitalization and helps validate our novel longitudinal approach. Figure 2 presents the marginal effects of digitalization on net hourly wages and the probability of unemployment at the time of the next interview for workers with varying levels of education.

We find a strong positive effect of increases in digitalization in an industry on the hourly net wages of workers with higher education levels, especially university degrees. At the same time, individuals with low levels of education or no qualifications experience a reduction in their hourly wages in periods when their industry digitalizes rapidly.[8] The coefficients can be interpreted as follows: a one unit increase in digitalization (1000 GBP ICT capital stock per worker) increases the average hourly net wage of a university graduate by 0.4 GBP which is equivalent to a yearly net wage increase of 768 GBP. By contrast, a one unit increase in digitalization decreases the average hourly wage of workers with no qualifications by 0.16 GBP or 312 GBP per year.

[8]We tested if the differences in the effect of digitalization across education groups are statistically significant. All of them are, except for the difference between no qualification and other qualification.

Figure 2: Effect of ICT capital stock increases on labor market outcomes



Note: Results show the marginal effect of one unit increase in digitalization (1000 GBP in ICT capital/worker) on hourly net wages (left) and the probability to become unemployed in percentage points (right).

Second, we study the effect of digitalization on employment status. In this case, we use lead models because we are interested in the probability of becoming unemployed in the future. We find some evidence that digitalization increases the likelihood that less educated workers report being unemployed when they are reinterviewed after digitalization occurred. This finding is in line with the task-based literature emphasizing that primarily routine jobs in the middle and low end of the wage and education distribution are susceptible to automation (Autor, Levy and Murnane, 2003). However, the effects are substantively small. For example, a one-unit increase in our measure of digitalization, i.e. a 1000 GBP increase in the ICT capital stock per worker (0.4 std), is associated with an increase in the probability to report being unemployed at the next interview of 0.24 percentage points for the no qualification group. This constitutes a 7% increase in the odds to become unemployed from 1:30 to 1:28.5. As noted above, a caveat is that we do not observe unemployment spells between interviews. The reported increase thus likely represents a lower bound estimate.

Our findings are in line with previous studies and suggests that our novel empirical approach is valid. For example, Autor, Dorn and Hanson (2015) conclude that digitalization has rather limited net employment effects despite its profound impact on the overall employment structure. For the UK, Kurer and Gallego (2019) show that most routine workers stay in their jobs and the decline in the share of routine jobs happens through retirement and lower entry rates rather than layoffs.

So far, the analysis yields two important take-away points. The impact of faster than average digitalization on hourly wages is positive for a majority of workers, but digitalization has unequal effects on highly and less educated workers. Those with a higher degree represent 39% of our sample in 2015 and are unambiguous economic winners, as digitalization increases their wages without any adverse employment effects. Adding workers holding A-Level certificates (upper secondary education), whose wage gains come at the cost of slightly increased unemployment risk, this share increases to 61% of the population. Workers with secondary education (GCSE and similar) make for about a fifth of the population and experience neither positive nor negative income effects from digitalization. Unambiguous economic losers of digitalization are concentrated in groups with low formal educational credentials, which account for about 20% of the population. In sum, digitalization first and foremost benefits those who have the skills to thrive in a rapidly world of work and reinforces patterns of wage polarization.

Digitalization and Political Outcomes

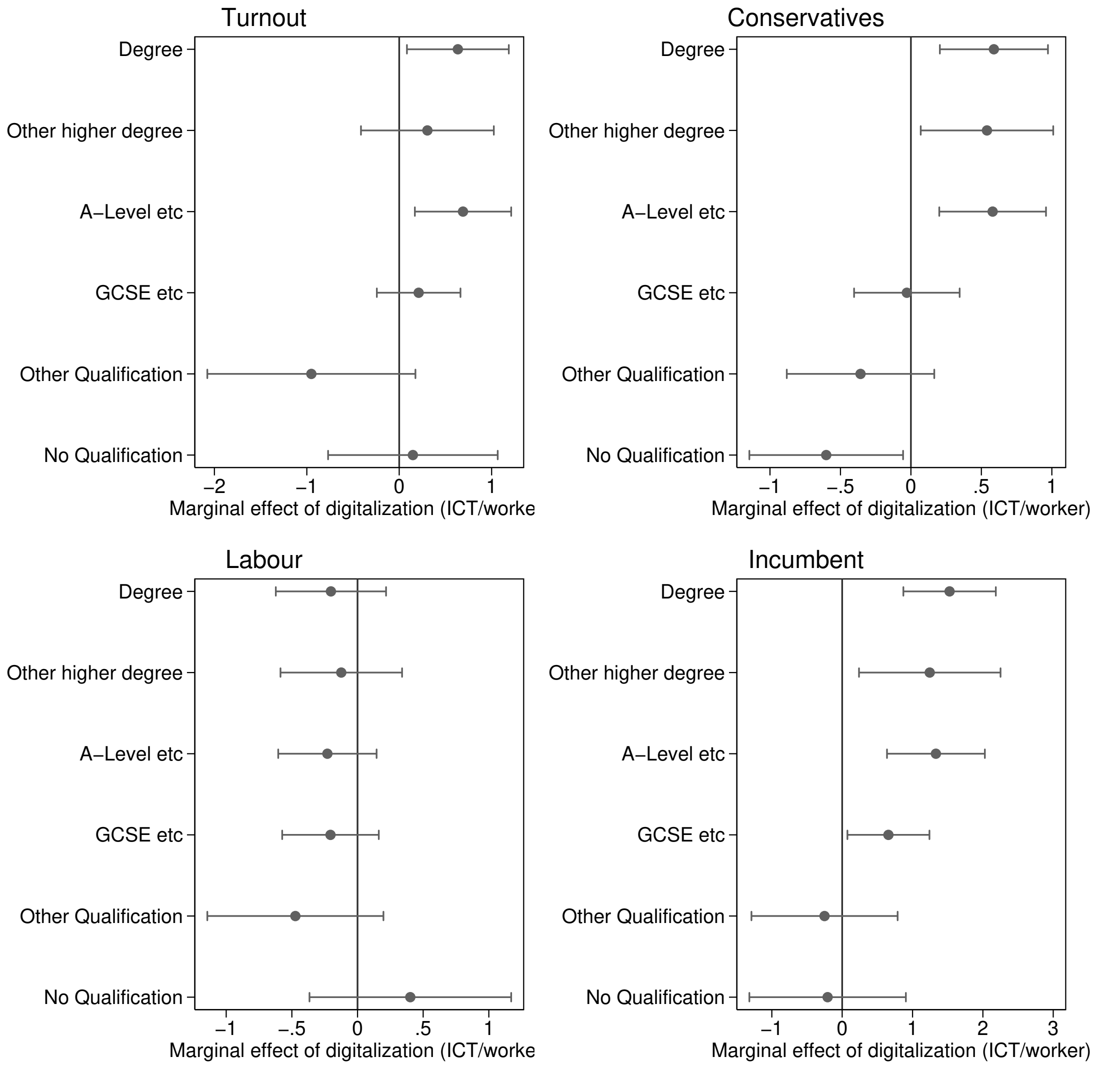
Our primary interest is in whether and how these distributive effects lead to changes in individual political behavior. Figure 3 presents the main results regarding voter turnout, support for the Conservative Party, for the Labour Party, and for the incumbent.

We find evidence of increasingly unequal political participation due to technological change. Highly educated workers in industries digitalizing more quickly become more likely to vote. A one unit increase in digitalization raises turnout among voters with university degrees by 0.64 percentage points. On the other hand, we find no effects or negative effects among less educated workers. Recent work has shown that the gaps in the turnout rates of citizens with high and low socio-economic status has increased over time in the UK (Heath, 2018). Our results suggest that digitalization contributes to increasing inequalities in voter turnout by (weakly) augmenting existing gaps.

Next, we examine the relationship between digitalization and support for parties. The results provide clear evidence for increased support for the Conservatives among winners of technological change. For example, a 1000 GBP increase in the capital stock per worker is associated with an increase in support for the Conservatives of approximately 0.6 percentage points among the highly educated. For less educated workers, digitalization is associated with a reduction in support for the Conservatives.[9]

[9] The differences in the effects of digitalization for workers with university degrees and workers of the three lower education groups are statistically significant at conventional levels. The same is true for the difference between the top three education groups and the no qualification group.

Figure 3: Effect of digitalization on political outcomes, industry-spells fixed effect specification



Note: Results show marginal effect of one unit increase in digitalization (1000GBP in ICT capital/worker) on the probability to report having voted or supporting a given political party. All results are in percentage points.

The results are consistent with our expectation that workers who benefit from digitalization become more likely to support an economically right-wing party which could be due to changes in economic preferences about redistribution. In line with other studies on economic shocks and voting behavior (see Margalit, 2019), the effect is limited in magnitude. Still, the reported effects are short-term and can accumulate over time, leading to more significant shifts in party support. Moreover, even modest changes in political behavior can be politically consequential as elections are often won by small margins.

With respect to support for the Labour Party, we do not find clear results. While the pattern is to some extent a weak mirror image of support for the Conservative party, the effects are small and imprecisely estimated. This is true even among less qualified workers, which contrasts with previous research suggesting that losers of digitalization ask for more redistribution (Thewissen and Rueda, 2017). However, it should be noted that our industry-spell fixed-effect approach may underestimate the effects on the behavior of losers of digitalization since our analyses only capture political reactions of workers who remain in the labor market (see section SI0.4.3 for an approach that includes displaced workers).

Finally, we also theorized effects on support for the incumbent that are analytically distinct from voting decisions based on support or opposition to redistribution. The main hypothesis in this case is that through a simple reward-punishment mechanism, winners of digitalization become more likely to support the incumbent while losers withdraw support. The lower right panel of Figure 3 reports marginal effects of digitalization on support for the incumbent party. The results provide clear-cut evidence in line with the egotropic economic voting hypothesis: Being in a digitalizing environment increases the likelihood to support the incumbent, but only for highly educated workers (who benefit more from digitalization).

Incumbency effect: Analysis by period

So far, our analysis finds that digitalization increases support for the Conservative party and for the incumbent among highly educated workers. In an attempt to distinguish between these two possibilities, we re-ran our analysis separately before and after the government change in May 2010.[10]

Table 1 shows that our results about political effects are mainly driven by the years after 2010. Column 1 shows that digitalization did not result in significantly increased support for the Labour party during their period in government (until 2010). Columns 6 and 7, on the other hand, speak in favor of an incumbency effect because the coefficients for incumbent voting are twice as large than for vote for Conservatives. Also, the Conservative Party did not benefit from digitalization when they were in opposition (pre-2010, column 4).

The findings are consistent with the interpretation that digitalization affects support for parties through two distinct mechanisms (spatial voting and economic voting), which can cancel each other out or

[10]Note that results are not driven by differential economic effects of digitalization before and after the Great Recession. Additional analyses presented in section SI0.3 in the Supplementary Information (SI) show that the estimates of the effects of digitalization on hourly wages and unemployment are comparable across periods.

Table 1: Sub-period Analysis: Until May 2010 and after May 2010

	Vote for Labour			Vote for Conservatives			Incumenbent
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pre May 2010	Post May 2010	Overall	Pre May 2010	Post May 2010	Overall	Overall
Degree × ICT	0.432	-0.694	-0.203	0.172	0.598	0.589**	1.527***
	(0.245)	(0.370)	(0.214)	(0.197)	(0.400)	(0.196)	(0.336)
Other higher degree × ICT	0.146	-0.313	-0.124	0.289	0.757	0.540*	1.245*
	(0.327)	(0.448)	(0.237)	(0.318)	(0.447)	(0.240)	(0.514)
A-Level etc × ICT	0.0302	-0.441	-0.229	0.425	0.717	0.580**	1.333***
	(0.233)	(0.386)	(0.191)	(0.222)	(0.377)	(0.193)	(0.355)
GCSE etc × ICT	0.0392	-0.406	-0.206	-0.181	0.563	-0.0288	0.657*
	(0.246)	(0.413)	(0.188)	(0.258)	(0.413)	(0.191)	(0.298)
Other Qualification × ICT	-0.240	-1.308*	-0.473	-0.402	0.650	-0.358	-0.251
	(0.443)	(0.645)	(0.345)	(0.331)	(0.609)	(0.268)	(0.534)
No Qualification × ICT	0.275	-0.528	0.402	-0.467	-0.601	-0.601*	-0.207
	(0.434)	(0.861)	(0.391)	(0.305)	(0.743)	(0.278)	(0.567)
Age	-0.393	0.143	0.128	0.0995	0.881	0.383	-0.730
	(0.339)	(0.521)	(0.268)	(0.275)	(0.462)	(0.226)	(0.409)
Age × Age	0.00420	-0.00959**	-0.00453*	-0.00198	-0.00561	-0.00330*	-0.000287
	(0.00270)	(0.00340)	(0.00182)	(0.00235)	(0.00300)	(0.00163)	(0.00317)
Constant	61.88***	64.76**	59.78***	13.02	0.508	11.99	81.14***
	(11.77)	(19.86)	(9.050)	(9.410)	(16.78)	(7.639)	(13.30)
Individual*Industry FE	X	X	X	X	X	X	X
Education Group 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	106387	114663	221050	106387	114663	221050	221050

Note: All results are in percentage points. Standard errors in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Liberal Democrats are coded as incumbent party during the 2010-2015 coalition government. We present, for each education group, the marginal effect of digitalization (direct effect + interaction effect). This allows readers to immediately infer what is the effect of digitalization among workers with a given education level: e.g. if a university degree holder working in a digitalizing industry starts earning X more than if this industry were not digitalizing. The standard approach proposed by Brambor, Clark and Golder (2006) involves including the main effect and interaction effects separately, which yields identical results. However, the coefficients would then be relative to the base category, i.e. we would compare affected workers with different education levels. Marginal effects on the other hand compare affected and non-affected workers with the same education level, and are better suited in a longitudinal framework because they emphasize within-person changes.

reinforce each other depending on the ideological profile of the party in power. Although both parties' relative position on the economic left-right axis has varied over time, the Tories have had a clearly more pronounced pro-market stance during the entire time span of our analysis (see Figure SI0.8 in the Supporting Information). Accordingly, when the Tories are in power, both mechanisms push in the same direction for winners of digitalization, resulting in more clear-cut effects. In contrast, when the Labour party is in power, winners of digitalization face a trade-off: on one hand, the improvements in their economic situation push them to vote for the incumbent. On the other side, this incumbent has policy positions on the economic left-right dimension that are not in line with their economic interest. Such tension may be smaller when Labour governments are in favor of promoting the advanced sectors of economy than under a more sharply left-wing party.

Do the left-behind turn to the populist right?

An important question attached to our primary focus on winners of digitalization is if the minority of workers who lose out in the same process politically respond by increasing support for populist or anti-system parties. Admittedly, our case and data is not ideal to fully examine this question: In a majoritarian electoral system, protest and populist parties are rarely electorally viable, making their political presence marginal. In the case of the UK, the UK Independence Party (UKIP) has been a fringe party over most of the period studied and support for UKIP has only been coded since 2013 in BHPS/UKHLS. Hence, the data available to examine this question is limited to the latest period.

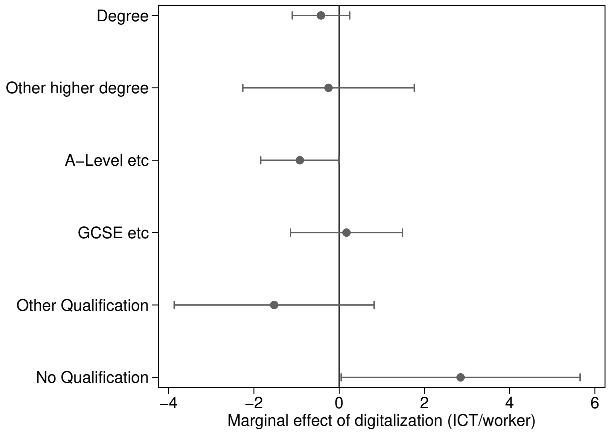
Nevertheless, our results, which should be interpreted with caution, support the possibility that the "left-behind" might turn to the populist right when their workplace digitalizes. Figure 4 shows marginal effects of digitalization on UKIP support. We find increased support among the small group of unambiguous losers of digitalization (the "no qualification" group is about 4% of our sample since 2013). This is consistent with previous findings that digitalization makes losers more likely to support anti-establishment parties (Im et al., 2019; Anelli, Colantone and Stanig, 2019; Kurer, 2020). The magnitude of the effect is impressive but it is very imprecisely estimated.[11] While the negative effect of digitalization on low-skilled workers' wages might rather suggest support for a pro-welfare party than for the populist right, the below section on attitudinal mechanisms offers some evidence that welfare chauvinism and competition for social expenditure might be part of the explanation.

Instrumental variables analysis

Since one might worry about endogeneity of our measure of digitalization, e.g. due to governmental policy support for specific sectors, we instrument ICT capital stocks in the UK with analogous data from the United States. Tables 2 and 3 present the results of the instrumental variables analysis next to the baseline results.

[11] A possible concern is that a large share of low-skilled workers has migration background, which in turn mutes right-wing populist support but Table SI0.11 in the SI shows that the results are substantively unchanged when excluding people born outside of the UK.

Figure 4: Effect of digitalization on UKIP support, industry-spells fixed effect specification



All economic and political results remain qualitatively unchanged, although the instrumental variable approach tends to produce larger point estimates. Obtaining larger IV estimates is not unusual and could be due to different reasons. A small part of the difference between our main specification and the IV can be attributed to differences in the sample used. EUKLEMS does not provide data for two industries in the USA (telecommunications and wholesale and repair of motor vehicles) resulting in a slightly smaller and more homogeneous sample. When we rerun the main analyses excluding these industries, the coefficients become somewhat closer to the IV results. Measurement error may also contribute to explain the larger IV coefficients if ICT capital stocks are better measured in a larger economy like the USA.

More substantively, the difference between the coefficients suggests that our measure of digitalization in the UK is indeed partly endogenous. One possible reason is that policy in the UK may work to limit the polarizing effects of digitalization on economic and political outcomes. Another reason could be that industrial policy in the UK might lead to an inefficient allocation of ICT investment across industries. Yet another explanation is related to trade unions pressure on firms to mitigate the strongest symptoms of digitalization on workers' material and psychological well-being. All three processes would result in attenuation bias in our main specification.

Robustness Checks

We run a series of robustness checks in order to rule out alternative interpretations and further concerns about endogeneity. Perhaps the most important concern with respect to the main findings relates

Table 2: Instrumental Variable Results: Economic Outcomes

	Hourly net wage		Probability to become unemployed	
	(1) Main specification	(2) Instrumental variable	(3) Main specification	(4) Instrumental variable
Degree × ICT	0.343***	0.435***	0.0129	0.241
	(0.0324)	(0.0808)	(0.0713)	(0.197)
Other higher degree × ICT	0.184***	0.301***	0.00620	0.354
	(0.0336)	(0.0745)	(0.0644)	(0.211)
A-Level etc × ICT	0.0514*	0.104	0.168**	0.421*
	(0.0229)	(0.0860)	(0.0608)	(0.203)
GCSE etc × ICT	-0.0114	-0.0477	0.183**	0.631
	(0.0185)	(0.0598)	(0.0686)	(0.413)
Other Qualification × ICT	-0.135***	-0.228**	0.0451	0.572*
	(0.0288)	(0.0876)	(0.0807)	(0.274)
No Qualification × ICT	-0.185***	-0.305***	0.227*	0.620
	(0.0398)	(0.0894)	(0.106)	(0.446)
Degree	-1.995***	-2.513***	0.883	1.496
	(0.209)	(0.308)	(0.793)	(1.257)
Other higher degree	-2.028***	-2.622***	1.446	1.549
	(0.218)	(0.294)	(0.778)	(1.174)
A-Level etc	-1.628***	-1.970***	0.607	1.169
	(0.156)	(0.250)	(0.691)	(1.094)
GCSE etc	-1.141***	-1.254***	0.773	0.741
	(0.147)	(0.218)	(0.657)	(1.183)
Other Qualification	-0.441**	-0.420	1.124	0.900
	(0.137)	(0.222)	(0.652)	(0.964)
Age	0.345***	0.346***	-0.435***	-0.442***
	(0.0271)	(0.0277)	(0.0994)	(0.101)
Age × Age	-0.00312***	-0.00311***	0.00158**	0.00166**
	(0.000212)	(0.000220)	(0.000604)	(0.000624)
Constant	-2.821***		13.76***	
	(0.797)		(3.681)	
Individual*Industry FE	X	X	X	X
Year FE	X	X	X	X
Region FE	X	X	X	X
Observations	179477	151642	216130	187153
First stage F-stat		104.6		90.11

Note: Probability to become unemployed is the probability of being unemployed at the time of the next interview (reported in percentage points). Standard errors in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

to the possibility that an increase in ICT capital investment simply reflects the fact that an industry is doing well and thus able to offer higher wages and better working conditions. This could invalidate the interpretation of our results since 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

Table 3: Instrumental Variable Results: Political Outcomes

	Turnout		Conservatives		Labour		Incumbent	
	(1) Main	(2) IV	(3) Main	(4) IV	(5) Main	(6) IV	(7) Main	(8) IV
Degree × ICT	0.635*	1.396*	0.589**	2.198**	-0.203	0.324	1.527***	2.877*
	(0.282)	(0.622)	(0.196)	(0.672)	(0.214)	(0.529)	(0.336)	(1.444)
Other higher degree × ICT	0.305	2.299*	0.540*	1.759*	-0.124	0.272	1.245*	2.365*
	(0.366)	(1.051)	(0.240)	(0.696)	(0.237)	(0.666)	(0.514)	(1.182)
A-Level etc × ICT	0.691**	1.998*	0.580**	1.513*	-0.229	-0.550	1.333***	2.683**
	(0.264)	(0.992)	(0.193)	(0.592)	(0.191)	(0.532)	(0.355)	(0.943)
GCSE etc × ICT	0.211	1.186	-0.0288	0.917	-0.206	0.464	0.657*	2.034*
	(0.231)	(0.983)	(0.191)	(0.657)	(0.188)	(0.598)	(0.298)	(0.952)
Other Qualification × ICT	-0.951	1.863	-0.358	1.468	-0.473	0.451	-0.251	2.645
	(0.575)	(1.860)	(0.268)	(0.996)	(0.345)	(0.975)	(0.534)	(1.776)
No Qualification × ICT	0.148	2.235	-0.601*	0.443	0.402	0.216	-0.207	0.556
	(0.470)	(3.140)	(0.278)	(1.073)	(0.391)	(1.761)	(0.567)	(2.138)
Degree	-0.617	2.391	-7.420***	-8.232**	2.319	0.601	-12.11***	-12.67*
	(3.336)	(6.396)	(1.937)	(3.101)	(2.371)	(4.350)	(3.591)	(6.092)
Other higher degree	-2.424	-2.807	-5.326**	-5.324	0.522	-0.803	-9.677*	-10.15
	(4.038)	(6.884)	(2.053)	(3.238)	(2.439)	(4.405)	(3.982)	(5.948)
A-Level etc	-5.519	-3.938	-6.227***	-5.190	0.879	1.462	-9.460**	-10.63*
	(2.846)	(5.948)	(1.786)	(2.762)	(2.164)	(4.043)	(3.136)	(5.152)
GCSE etc	-4.484	-2.404	-3.577*	-3.018	1.581	-0.428	-9.527**	-10.57*
	(2.881)	(5.919)	(1.744)	(2.822)	(2.028)	(3.919)	(3.147)	(5.088)
Other Qualification	0.548	-1.107	-0.00495	-1.629	-0.495	-3.125	-1.458	-6.587
	(2.274)	(6.176)	(1.703)	(2.942)	(1.824)	(3.600)	(2.602)	(4.909)
Age	-1.143**	-1.112**	0.383	0.354	0.128	0.189	-0.730	-0.739
	(0.390)	(0.404)	(0.226)	(0.232)	(0.268)	(0.274)	(0.409)	(0.417)
Age × Age	-0.00913***	-0.00951**	-0.00330*	-0.00276	-0.00453*	-0.00531**	-0.000287	0.000314
	(0.00264)	(0.00290)	(0.00163)	(0.00170)	(0.00182)	(0.00191)	(0.00317)	(0.00325)
Constant	133.1***		11.99		59.78***		81.14***	
	(12.47)		(7.639)		(9.050)		(13.30)	
Individual*Industry FE	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
Observations	103739	81054	221050	187899	221050	187899	221050	187899
First stage F-stat		109.9		86.76		86.76		86.76

Note: All outcomes are in percentage points. Standard error in parenthesis are clustered at the individual level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

additional analysis using *non-ICT investments* as the main explanatory variable. Non-ICT investments are simply the sum of all assets minus our three ICT categories (capital stocks in computing equipment, communications equipment, and computer software and databases) divided by employees. (We discuss different disaggregations of the residual asset categories in the Supplementary Information.) Changes in an industry's non-ICT capital stock per worker do not predict any of the outcomes we are interested in, suggesting that our results specifically capture the consequences of digitalization rather than a thriving industry.

Further analysis deal with potential outliers (e.g. rapidly digitalizing industries or regions); additional controls for trade exposure to isolate the impact of technology; different fixed-effects structures and clustering at the industry instead of the individual level. In addition, we replicated all analyses using lead models to better capture negative effects on workers who lose their job and hence drop out of the labor force. Finally, we have a closer look at attrition. Overall, the result of the robustness checks are reassuring. We can recover our substantive results in all of these additional models. We present a more detailed description of both the empirical concerns and our proposed remedy including full regression tables in the Supplementary Information (section SI0.4).

Mechanisms

The causal chain underlying our argument assumes three steps, namely that (i) digitization creates winners and losers through its differential impact on wages and employment along an education gradient. These distributive consequences (ii) affect individuals political preferences and attitudes, which leads beneficiaries of digitalization to (iii) voting for conservative parties, voting for the incumbent, and higher turnout rates. We have provided robust evidence for (i) and (iii) in the above analysis.

As a final step, we assess some attitudinal mechanisms possibly linking digitalization's implications to electoral behavior. To be clear, our panel data is not ideally suited to trace attitudinal mechanisms. The number of questions on preferences and subjective perceptions of respondents is small and they are infrequently included, as most attitudes are only asked in a few waves. The few questions asked repeatedly are imperfect indicators of the theoretical concepts of interest, introducing measurement error, which attenuates results and is particularly relevant in a longitudinal analysis. This final auxiliary analysis helps us assess the plausibility of attitudinal channels, but it is not powerful enough to clearly refute any of them.

We argued that workplace digitalization can increase support for right-wing parties through a change in preferences for economic policies if winners of digitalization become less likely to support a redistributive welfare state. Additionally, we argued that digitalization can increase support for the incumbent party if winners become more satisfied in general and more supportive of whoever is in government. For both processes, we anticipate the opposite reaction for losers. We operationalize preferences about economic policies through a battery about preferences for state intervention which asks about governments' capacity to solve economic problems and their obligation to provide jobs, and satisfaction with a question asking respondents about general life satisfaction. The exact wording and results figures are provided in the Supplementary Information.

Digitalization is associated with at best small changes in life satisfaction, but we do observe a clear pattern of divergence between winners and losers. Workers with no formal qualification become significantly less satisfied compared to all workers who hold at least a GCSE when their sector digitalizes ($p < 0.01$). This divergence mirrors the pattern with respect to incumbency support.

We find support for the claim that digitalization reduces support for state intervention in the economy among university degree holders. This result is consistent with the possibility that very skilled workers, the main economic beneficiaries of digitalization, adjust their economic preferences in a more pro-market direction, which makes them increasingly attracted to the Tories' program. However, we also find an unexpected result: the group with the lowest qualifications, i.e. unambiguous losers of digitalization, also seem to become less supportive of state intervention. A plausible explanation in light of this specific group's support for UKIP (see Figure 4) might be related to the particular social policy position of many right-wing populist parties who strongly differentiate between deserving segments of society (veterans, elderly, "ordinary people") and the rest (Fenger, 2018). Indeed, UKIP has been shown to support insurance-based welfare interventions, especially pensions, but in general opposes a more equity-based, universalist expansion of the welfare state (Ennser-Jedenastik, 2018). It is possible that concerns about deservingness and competition for increasingly scarce welfare benefits is reflected among the lowest skilled group's critical stance on general state intervention that benefits the broader population.

Lastly, we also tested a competing mechanism, namely that digitalization may affect political preferences through changes in attitudes about non-economic issues. It has long been argued that economic modernization and rising living standards increase the importance of non-material goods and help spread social progressiveness on issues such as gender, the environment, or gay rights (Inglehart, 1977). This argument is in conflict with our finding of increased support for the Conservative party and lead us to test the competing hypothesis that increases in digitalization make workers more liberal on social issues. Note that the prediction, if this mechanism holds, would be a shift of winners towards socially progressive parties, such as Labour or the LibDems rather than the Conservative Party. The best suited indicator of socially progressive attitudes available for a sufficiently large number of years in our data is an item battery on support for gender equality. Interestingly, but in line with our main results, we do not find any evidence that changes in digitalization affect progressiveness about gender issues among skilled beneficiaries.

This final result clashes with a common depiction of digitalization winners in the media: the socially progressive celebrity tech entrepreneurs or creators of innovative start-up companies in dynamic urban areas. It is worth reiterating at this point that our analysis is not concerned with such exceptional beneficiaries. We do not study superstars and we do not primarily cover individuals who self-select into thriving technology industries. Our analysis is concerned with the large but less visible group of regular beneficiaries of new technologies who continue to work in their factories, laboratories and offices, become more productive when new digital tools are introduced at their workplace, and benefit from limited but steady improvements of their material conditions.

Our analysis of wage effects has provided strong support for an economic channel linking digitalization and political behavior. Moreover, in light of our auxiliary results on attitudinal variables, an economic voting mechanism seems plausible. Reflecting the polarization of wages, we find a gradient in life satisfaction between winners and losers of digitalization. Furthermore, winners' relatively stable economic situation makes them less supportive of state intervention, especially compared to semiskilled workers with more ambiguous economic prospects. This aspect may help explain their tendency to lean towards center-right rather than center-left incumbents. Finally, we do not find any evidence of particularly progressive values on the cultural dimension. Taken together, ordinary winners of digitzalization are unspectacular supporters of the status quo. For them, mainstream pro-market parties, especially those in government, are a reasonable choice on election day.

Discussion

The digital revolution is accompanied by two fears: that many workers will be displaced from their jobs and that this will lead to political unrest. Public debate and the scarce academic literature on this topic has primarily been concerned with its downsides and focused on the losers of technological progress. While this focus is comprehensible in light of recent political disruptions, we contend that this one-sided attention is at odds with standard economic theories emphasizing productivity gains as well as with historical experience, which has proved many gloomy projections wrong.

We document both economic and political effects of digitalization. Contrary to pessimistic accounts, a majority of workers benefit economically from rapid digitalization in their industries. Yet, these benefits are not equally distributed and they disproportionately accrue to the highly educated. Our most novel finding is that these diverging economic trajectories are mirrored in diverging political trajectories. First of all, regarding party choice, the beneficiaries of digitalization become more likely to support the Conservative Party, in particular when they are the incumbent party. Second, with respect to turnout, we observe that digitalization reinforces inequalities along education lines: The highly educated turn out more to vote if their sector digitalizes whereas we do not find such mobilizing effects among the less educated. The large but often neglected pool of voters who benefit from technological innovation thus seems willing to support mainstream parties and uphold the existing social contract.

There are several reasons why our results are more optimistic than previous work. First of all, we look at the effects of a general-purpose technology (ICT) on the workforce. This approach is likely to produce different results than if we had focused on more specific technologies, such as industrial robots, that may have particularly strong displacement effects. Indeed, Acemoglu and Restrepo (2020) show that industrial robots have strong negative effects on employment and wages, whereas the effects of increases in other ICT capital, such as computers per worker or investment in software and computers, are often *positive*. Clearly, some technologies have stronger labor-displacement effects, and possibly political effects, than others. We see our contribution as an important complement to studies with a focus on technologies with a more concentrated and more unequivocally negative impact on employment. Our approach allows us to include all sectors rather than mostly manufacturing, a sector which has seen particularly sharp reductions in employment in advanced economies, but is overall rather small (according to the Office for National Statistics, the UK share of people in manufacturing is below 10%). Our coverage of all sectors with a general measure of digitalization possibly facilitates identifying gains of technological change and results in a more optimistic picture.

Another reason why our conclusions may be relatively optimistic is related to our empirical approach. We study the political implications of digitalization on the active labor force, not on the population as a whole, and we focus on individual effects, which can differ from contextual effects. Using a longitudinal approach, we find little indication of political unrest among regular workers. We do not include in our sample retired or disabled people, students or people doing housework, even though workplace digitalization may affect them through various channels including the changes in communities and spillovers within the household. Some segments of this population might react more negatively, e.g.

workers who lose their job and cannot find a new one or young citizens with troubles entering the labor market in the first place, although the size of these groups is too small to produce large differences. For these reasons, we do not make inferences based on our findings to population-wide political effects.

To conclude, our findings reveal a complex picture of the political consequences of digitalization. The innovative empirical analysis provides abundant and robust evidence that digitalization is economically beneficial for a majority of the labor force and is politically consequential in two contrasting ways: First, the large group of winners become more likely to support incumbent mainstream parties and thus can act as a stabilizing force in democratic systems. Second, while we only find weak evidence of an anti-establishment backlash among unskilled workers as a reaction to digitalization, we demonstrate that the economic polarization associated with digitalization is accompanied by differential political effects on winners and losers of this process. The resulting divergence in political behavior between the two groups might translate quite directly into increasing political polarization.

For good reasons, much of the reporting on recent political disruptions like Brexit has been on the grievances among the disadvantaged and the likely reasons for their support of leaving the European Union. The Brexit vote should certainly be attributed to a wide range of causes, but it is plausible that the economic and political polarization between beneficiaries of digitalization and other citizens we document in this paper generated political alienation among a subset of the electorate that is exposed to the downsides of economic modernization. While the group of clear-cut losers of digitalization in absolute terms is small, a larger segment of the population in the lower middle class is confronted with relative decline as they observe how others thrive in a digital world while they themselves stagnate.

At the same time, our results remind us that the emergence of anti-establishment forces in most advanced capitalist democracies up to now remains a minority phenomenon. Certainly, how large exactly that minority grows is a question of crucial importance and in some cases, most notably Brexit, anti-establishment forces even managed to mobilize a tight majority of the population. Nevertheless, even in exceptionally disruptive events like Brexit, there was a less attention-grabbing but equally sized group of Remainers who seem content with current circumstances and support the political status quo. All in all, we thus contend that the implications of digitalization at the workplace are more multi-faceted than the narrative of the "revenge of the left-behind" suggests.

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Supplementary Information

Contents

SI0.1 Description of the data

SI0.1.1 Summary Statistics

Table SI0.1: Summary Statistics

	count	mean	sd	min	max
Year	288009	2009.45	5.40	1997	2018
Turnout	108558	0.71	0.46	0	1
Conservatives	233521	0.22	0.41	0	1
Labour	233521	0.33	0.47	0	1
Liberal Democratic Party	233521	0.10	0.29	0	1
UKIP	65920	0.45	0.21	0	1
Incumbent	233521	0.31	0.46	0	1
Industry ID from EUKELMS.	288009			1	38
ICT	257241	3.71	4.58	0.10	47.46
Non-ICT machinery capital stock	257241	27.87	44.20	2.20	540.77
Non-ICT capital stock	257241	133.43	392.35	6.46	4955.94
ICT stock USA / workers in UK	250883	50.28	147.52	0.33	1771.66
Imports in goods from China	40365	9.22	20.77	0.01	189.74
Government region ID	287157			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	1789.68	984.44	324	4096
Education level	288009	4.08	1.52	1	6
Hourly net wage	201830	9.48	5.39	0.00	100.80
Becomes unemployed	224907	0.02	0.15	0	1
Above median RTI	267833	0.47	0.50	0	1
Supports government intervention PCA	69004	-0.06	1.03	-3.22	2.90
Social progressiveness PCA	146729	0.24	1.32	-3.34	3.04
Life satisfaction	262063	5.22	1.28	1	7
Total observations	288009				

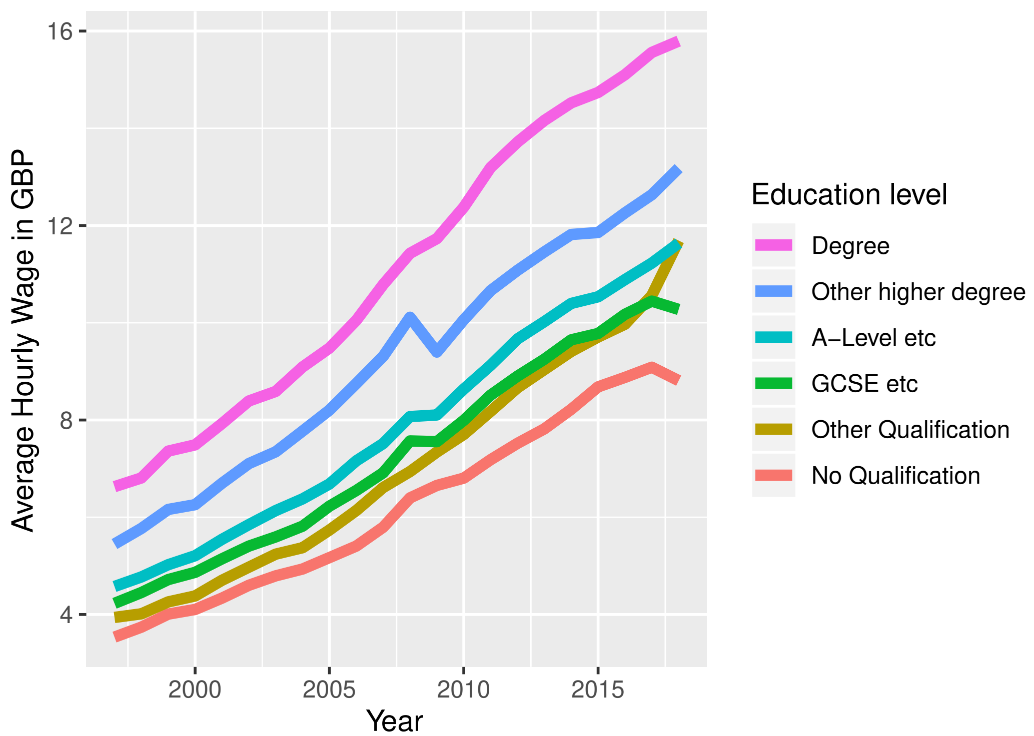
Note: ICT defined as "real fixed ICT capital stock (in 1000 GBP or USD, respectively, in constant 2010 prices) normalized by number of employees". The Supplementary Information to this article contains a detailed description of the evolution of all dependent variables over time for each educational group.

SI0.1.2 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 SI0.1 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 SI0.2 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

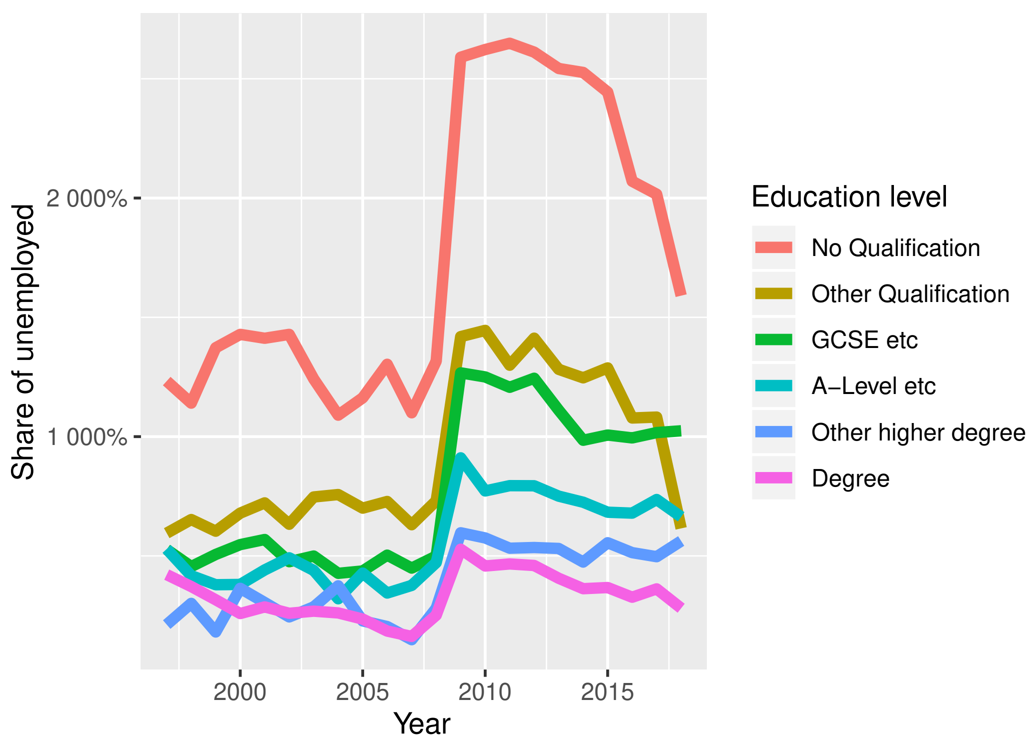
Figure SI0.1: Average hourly net wage by education



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.

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.

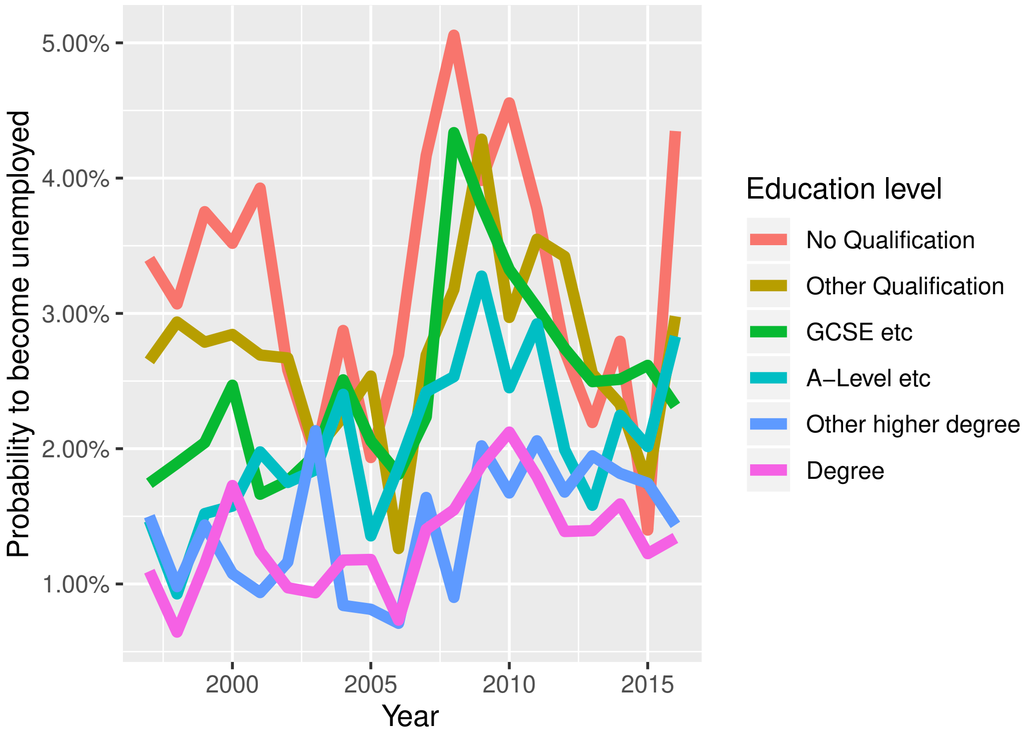
Figure SI0.2: Share unemployed by education



Note: Share unemployed at the time of the interview.

Figure SI0.3 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 SI0.3: 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.

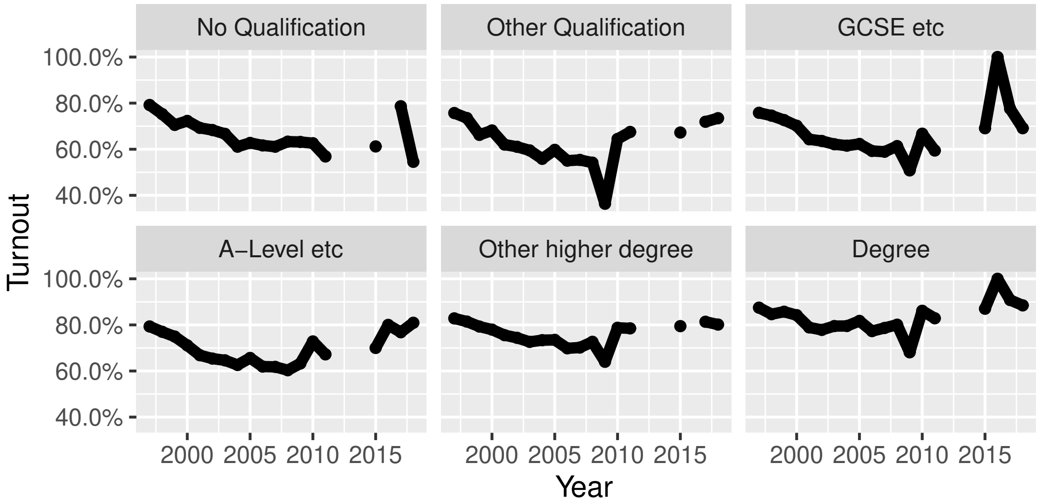
Figure SI0.4 plots reported turnout for different education levels. Note that this was only asked infrequently after 2008. There was a steady decline in turnout until the mid 2000s and then a partial recovery. Turnout is consistently higher for the highly educated.

Figure SI0.5 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 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.

SI0.1.3 Crosswalking and Merging Data Sets

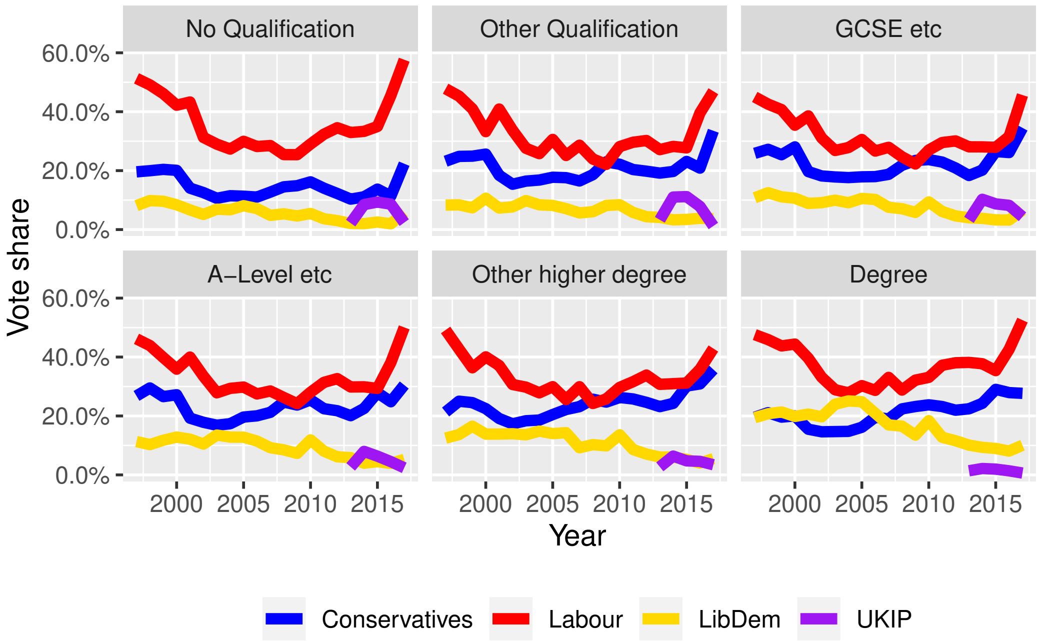
The BHPS, UKHLS and the EU KLEMS datasets are provided using different classifications, which we address by constructing cross-walks. We are able to match the 2007 version of the Standard Industrial Classification (SIC07), used between 2009 and 2015 comprehensively to the classification scheme used by EU KLEMS (NACE

Figure SI0.4: 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.

Figure SI0.5: 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.

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.

SI0.2 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.

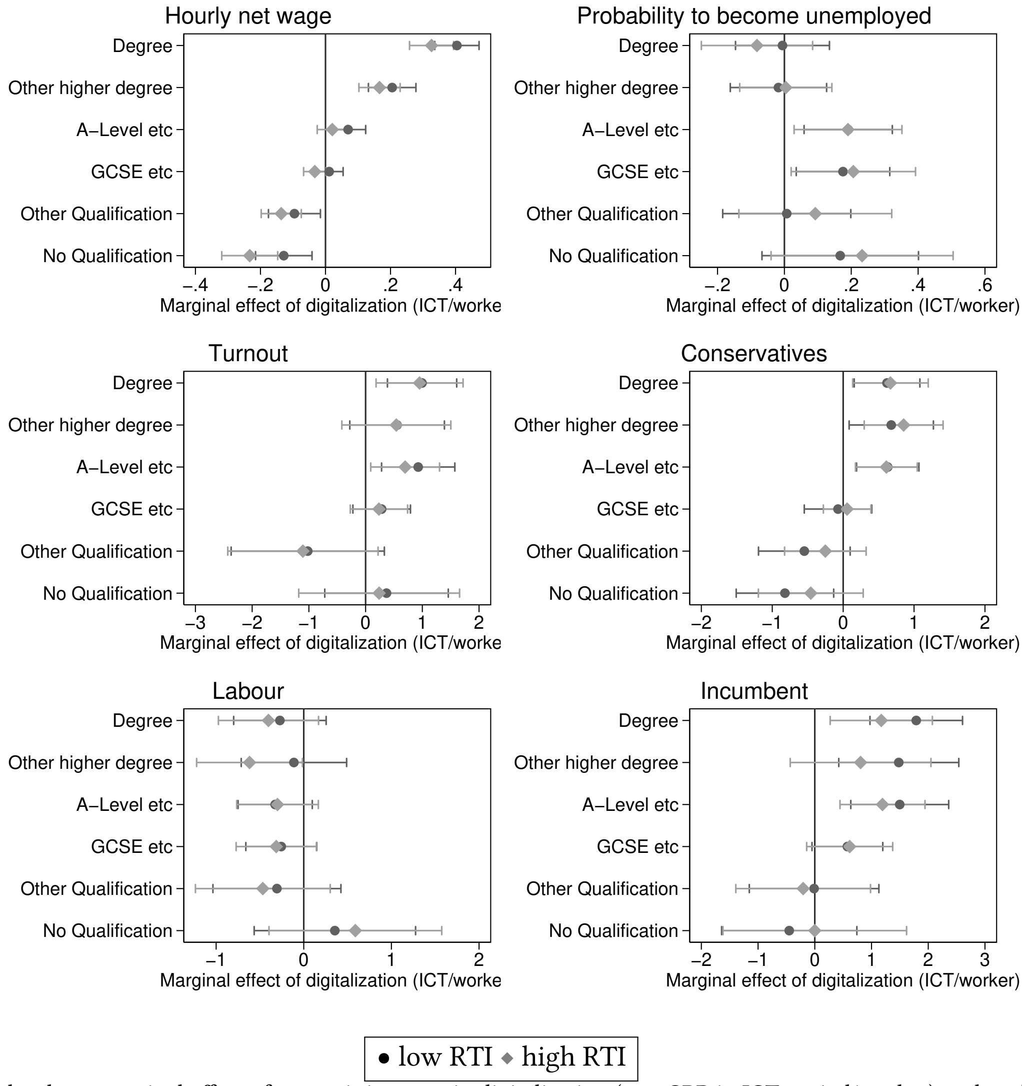
Specifically, we created occupation-specific RTI scores from ONET data following the standard approach of Autor and Dorn (2013), i.e. subtracting log abstract and log manual content from log routine content of each occupation, and relying on a crosswalk by Hardy and colleagues (2018) to merge data with 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 SI0.6 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 SI0.6: 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.

SI0.3 Economic Effects Before and After the 2010 Government Change

Table SI0.2 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. Main difference seems to be that in the 2010 onward period, low educated workers did not seems 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 SI0.2: 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	0.327***	0.302***	-0.0641	0.108
	(0.0350)	(0.0484)	(0.113)	(0.124)
Other higher degree × ICT	0.169***	0.207***	-0.138	0.0625
	(0.0479)	(0.0431)	(0.0843)	(0.140)
A-Level etc × ICT	0.0518	0.103*	0.221*	0.297*
	(0.0274)	(0.0424)	(0.110)	(0.147)
GCSE etc × ICT	-0.0300	0.0894*	0.222*	0.189
	(0.0216)	(0.0392)	(0.102)	(0.173)
Other Qualification × ICT	-0.116**	-0.00793	0.0620	-0.00930
	(0.0371)	(0.0612)	(0.119)	(0.209)
No Qualification × ICT	-0.206***	-0.0381	0.229	0.172
	(0.0490)	(0.0693)	(0.131)	(0.237)
Degree	-1.387***	-1.800***	3.188*	-0.509
	(0.242)	(0.353)	(1.352)	(1.778)
Other higher degree	-1.442***	-1.773***	4.476**	0.934
	(0.273)	(0.323)	(1.427)	(1.581)
A-Level etc	-1.265***	-1.257***	1.406	-0.571
	(0.164)	(0.293)	(1.085)	(1.550)
GCSE etc	-0.765***	-1.089***	1.797	-0.264
	(0.167)	(0.278)	(1.098)	(1.447)
Other Qualification	-0.333*	-0.491	1.541	1.486
	(0.142)	(0.251)	(0.926)	(1.547)
Age	0.339***	0.455***	-0.250	-0.367
	(0.0281)	(0.0487)	(0.130)	(0.206)
Age × Age	-0.00296***	-0.00422***	-0.000344	0.00118
	(0.000261)	(0.000329)	(0.000962)	(0.00133)
Constant	-3.759***	-1.880	6.771	14.92
	(0.871)	(1.757)	(4.142)	(8.167)
Id*Ind FE	X	X	X	X
Year FE	X	X	X	X
Region	X	X	X	X
Observations	85782	93695	100612	115518

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.4 Robustness checks in detail

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

SI0.4.1 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.

SI0.4.2 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 the tables presented in the SI 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.

SI0.4.3 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.[12] 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. 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.

SI0.4.4 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, Dorn and Hanson, 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.[13] 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 unchanged when controlling for changes in trade within the industries for which data are available.

SI0.4.5 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

[12] 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.

[13] 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.

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 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 SI0.3: 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	0.343***	0.435***	-0.000809	0.331***	0.432***	0.307***	0.153***	0.478***	0.133***
	(0.0324)	(0.0809)	(0.000705)	(0.0307)	(0.0410)	(0.0349)	(0.0161)	(0.0802)	(0.00866)
Other higher degree × ICT	0.184***	0.301***	-0.000485	0.182***	0.225***	0.174***	0.109***	0.328***	0.104***
	(0.0336)	(0.0745)	(0.000539)	(0.0331)	(0.0435)	(0.0337)	(0.0165)	(0.0627)	(0.00921)
A-Level etc × ICT	0.0514*	0.104	-0.000726	0.0496*	0.0824*	0.0651*	0.0720***	0.124*	0.131***
	(0.0229)	(0.0860)	(0.000449)	(0.0227)	(0.0362)	(0.0255)	(0.0143)	(0.0542)	(0.00787)
GCSE etc × ICT	-0.0114	-0.0477	-0.000728	-0.0141	-0.00711	-0.00707	0.0462***	0.0119	0.114***
	(0.0185)	(0.0598)	(0.000432)	(0.0185)	(0.0282)	(0.0208)	(0.0130)	(0.0422)	(0.00808)
Other Qualification × ICT	-0.135***	-0.228**	-0.00109*	-0.141***	-0.145***	-0.122***	0.0300	-0.0968	0.0972***
	(0.0288)	(0.0876)	(0.000498)	(0.0286)	(0.0347)	(0.0305)	(0.0177)	(0.0588)	(0.0105)
No Qualification × ICT	-0.185***	-0.305***	-0.00128**	-0.188***	-0.212***	-0.109**	-0.00863	-0.224*	0.0351**
	(0.0398)	(0.0894)	(0.000444)	(0.0391)	(0.0500)	(0.0415)	(0.0209)	(0.0965)	(0.0112)
Degree	-1.995***	-2.513***	-0.679***	-1.953***	-2.243***	-1.675***	-1.125***	-2.793***	4.712***
	(0.209)	(0.308)	(0.178)	(0.209)	(0.225)	(0.215)	(0.169)	(0.628)	(0.0457)
Other higher degree	-2.028***	-2.622***	-1.242***	-2.019***	-2.148***	-1.876***	-1.603***	-2.733***	2.714***
	(0.218)	(0.294)	(0.179)	(0.219)	(0.232)	(0.227)	(0.177)	(0.702)	(0.0442)
A-Level etc	-1.628***	-1.970***	-1.276***	-1.604***	-1.707***	-1.496***	-1.409***	-1.899***	1.584***
	(0.156)	(0.250)	(0.130)	(0.158)	(0.171)	(0.162)	(0.135)	(0.363)	(0.0373)
GCSE etc	-1.141***	-1.254***	-0.903***	-1.128***	-1.179***	-0.978***	-1.000***	-1.492***	0.976***
	(0.147)	(0.218)	(0.127)	(0.150)	(0.158)	(0.148)	(0.130)	(0.358)	(0.0351)
Other Qualification	-0.441**	-0.420	-0.448***	-0.408**	-0.458**	-0.395**	-0.521***	-0.490	0.436***
	(0.137)	(0.222)	(0.112)	(0.137)	(0.144)	(0.135)	(0.118)	(0.332)	(0.0419)
Age	0.345***	0.346***	0.391***	0.374***	0.343***	0.334***	0.369***	0.235***	0.446***
	(0.0271)	(0.0277)	(0.0280)	(0.0275)	(0.0271)	(0.0316)	(0.0260)	(0.0588)	(0.00527)
Age × Age	-0.00312***	-0.00311***	-0.00331***	-0.00315***	-0.00307***	-0.00345***	-0.00332***	-0.00184***	-0.00454***
	(0.000212)	(0.000220)	(0.000217)	(0.000212)	(0.000213)	(0.000241)	(0.000190)	(0.000431)	(0.0000678)
Imports								-0.00292	
								(0.00331)	
Dummy=1 if person identifies as female									-1.189***
									(0.0210)
Constant	-2.821***	-2.585**	-3.960***	-3.439***	-2.667***	-1.817*	-3.356***	-0.642	-7.709***
	(0.797)	(0.832)	(0.850)	(0.845)	(0.799)	(0.873)	(0.777)	(1.756)	(0.145)
Individual*Industry FE	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	179477	174723	179477	179477	176659	153751	178458	32817	179477

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 SI0.4: 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	0.0129	0.241	0.000297	0.0157	-0.0849	0.124	0.0715	-0.0231	0.0182
	(0.0713)	(0.197)	(0.000635)	(0.0711)	(0.0812)	(0.0816)	(0.0454)	(0.120)	(0.0246)
Other higher degree × ICT	0.00620	0.354	0.000337	0.0161	-0.0601	0.0601	0.0713	-0.198	0.0201
	(0.0644)	(0.211)	(0.000602)	(0.0646)	(0.101)	(0.0764)	(0.0692)	(0.147)	(0.0289)
A-Level etc × ICT	0.168**	0.421*	0.000642	0.180**	0.152*	0.122	0.159**	0.0697	0.0190
	(0.0608)	(0.203)	(0.000689)	(0.0612)	(0.0711)	(0.0926)	(0.0533)	(0.139)	(0.0280)
GCSE etc × ICT	0.183**	0.631	0.000129	0.186**	0.176	0.257**	0.101	0.112	-0.00192
	(0.0686)	(0.413)	(0.000664)	(0.0686)	(0.0917)	(0.0843)	(0.0518)	(0.134)	(0.0296)
Other Qualification × ICT	0.0451	0.572*	0.000118	0.0496	0.00768	0.0158	-0.0195	-0.368	-0.0196
	(0.0807)	(0.274)	(0.00125)	(0.0807)	(0.0924)	(0.109)	(0.0864)	(0.195)	(0.0437)
No Qualification × ICT	0.227*	0.620	0.000146	0.225*	0.241	0.259	-0.0423	0.0821	-0.0628
	(0.106)	(0.446)	(0.00111)	(0.106)	(0.138)	(0.149)	(0.0903)	(0.168)	(0.0462)
Degree	0.883	1.496	0.208	0.872	1.203	0.258	-2.162*	3.255	-2.314***
	(0.793)	(1.258)	(0.739)	(0.794)	(0.817)	(0.946)	(0.840)	(2.059)	(0.214)
Other higher degree	1.446	1.549	0.812	1.450	1.655*	1.393	-1.199	3.775	-1.927***
	(0.778)	(1.174)	(0.726)	(0.776)	(0.817)	(0.934)	(0.856)	(2.972)	(0.222)
A-Level etc	0.607	1.169	0.465	0.593	0.685	0.750	-0.855	0.563	-1.765***
	(0.691)	(1.094)	(0.634)	(0.691)	(0.720)	(0.846)	(0.743)	(1.525)	(0.217)
GCSE etc	0.773	0.741	0.676	0.757	0.835	0.499	-0.478	0.657	-1.093***
	(0.657)	(1.183)	(0.596)	(0.655)	(0.692)	(0.810)	(0.711)	(1.809)	(0.217)
Other Qualification	1.124	0.900	0.625	1.089	1.238	1.561*	-0.0571	2.275	-0.702**
	(0.652)	(0.964)	(0.584)	(0.653)	(0.670)	(0.764)	(0.709)	(1.985)	(0.259)
Age	-0.435***	-0.442***	-0.435***	-0.441***	-0.445***	-0.195	-0.580***	-0.383	-0.468***
	(0.0994)	(0.101)	(0.102)	(0.102)	(0.100)	(0.111)	(0.106)	(0.253)	(0.0238)
Age × Age	0.00158**	0.00166**	0.00152*	0.00154*	0.00154*	0.00259***	0.00407***	0.00217	0.00489***
	(0.000604)	(0.000624)	(0.000602)	(0.000604)	(0.000606)	(0.000719)	(0.000600)	(0.00172)	(0.000275)
Imports								0.00529	
								(0.0140)	
Dummy=1 if person identifies as female									-0.530***
									(0.0749)
Constant	13.76***	13.16***	14.68***	14.41***	14.13***	3.520	17.79***	-0.382	13.11***
	(3.681)	(3.827)	(3.792)	(3.811)	(3.712)	(3.300)	(3.691)	(8.508)	(0.641)
Individual*Industry FE	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	216130	210708	216130	216130	213075	183311	214741	34841	216130

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 SI0.5: Voted in last general elections

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Main	IV	Placebo	Region*Year FE	Excl. outliers	Lead	ID FE	Trade	Cross Sect
Degree × ICT	0.635*	1.396*	0.00864	0.562*	1.005**	0.353	0.364*	0.349	-0.00195
	(0.282)	(0.623)	(0.00540)	(0.281)	(0.376)	(0.280)	(0.153)	(0.725)	(0.110)
Other higher degree × ICT	0.305	2.299*	0.00726	0.293	0.806	0.656	0.230	0.145	-0.145
	(0.366)	(1.052)	(0.00458)	(0.364)	(0.553)	(0.397)	(0.187)	(0.629)	(0.132)
A-Level etc × ICT	0.691**	1.998*	0.00704	0.718**	0.976**	1.073***	0.460**	-0.0351	0.175
	(0.264)	(0.992)	(0.00644)	(0.264)	(0.365)	(0.290)	(0.153)	(0.558)	(0.116)
GCSE etc × ICT	0.211	1.186	-0.00261	0.180	-0.235	0.295	0.335*	0.0326	0.164
	(0.231)	(0.983)	(0.00524)	(0.229)	(0.396)	(0.256)	(0.155)	(0.508)	(0.119)
Other Qualification × ICT	-0.951	1.863	-0.00671	-1.000	-0.839	-0.180	0.207	-2.007	-0.430*
	(0.575)	(1.860)	(0.00766)	(0.575)	(0.558)	(0.417)	(0.251)	(1.240)	(0.182)
No Qualification × ICT	0.148	2.235	0.00204	0.205	0.277	0.536	0.637*	-1.262	0.342
	(0.470)	(3.141)	(0.00570)	(0.468)	(0.672)	(0.489)	(0.265)	(0.810)	(0.189)
Degree	-0.617	2.391	-0.874	-0.274	-1.302	-2.443	-1.022	-18.41	22.60***
	(3.336)	(6.397)	(3.257)	(3.334)	(3.436)	(3.478)	(2.900)	(9.758)	(0.723)
Other higher degree	-2.424	-2.807	-3.678	-2.658	-3.241	-5.876	-3.094	-22.62*	15.12***
	(4.038)	(6.886)	(3.821)	(4.016)	(4.215)	(4.131)	(3.439)	(11.41)	(0.782)
A-Level etc	-5.519	-3.938	-5.114	-5.339	-5.875*	-6.698*	-3.732	-14.13*	10.94***
	(2.846)	(5.949)	(2.719)	(2.836)	(2.958)	(2.932)	(2.540)	(6.130)	(0.704)
GCSE etc	-4.484	-2.404	-4.343	-4.265	-3.445	-4.106	-5.122*	-9.008	6.196***
	(2.881)	(5.920)	(2.750)	(2.871)	(3.041)	(3.081)	(2.488)	(6.064)	(0.695)
Other Qualification	0.548	-1.107	-1.092	0.888	0.771	1.274	-0.848	5.268	2.753**
	(2.274)	(6.177)	(2.029)	(2.243)	(2.314)	(2.373)	(1.811)	(5.314)	(0.844)
Age	-1.143**	-1.112**	-0.505	-0.553	-1.185**	0.455	-1.002**	-2.001*	1.979***
	(0.390)	(0.404)	(0.396)	(0.396)	(0.393)	(0.398)	(0.354)	(0.945)	(0.0801)
Age × Age	-0.00913***	-0.00951**	-0.00981***	-0.00947***	-0.00870**	-0.00968***	-0.00919***	-0.000692	-0.0114***
	(0.00264)	(0.00290)	(0.00263)	(0.00263)	(0.00266)	(0.00272)	(0.00229)	(0.00631)	(0.000959)
Imports								-0.0674	
								(0.0619)	
Dummy=1 if person identifies as female									0.152
									(0.302)
Constant	133.1***	129.5***	112.8***	113.5***	134.2***	80.16***	125.5***	162.7***	14.20***
	(12.47)	(14.40)	(12.88)	(12.91)	(12.60)	(13.44)	(12.47)	(31.78)	(2.202)
Individual*Industry FE	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	103739	100881	103739	103739	102060	91381	102642	19183	103739

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 SI0.6: 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	0.589**	2.198**	0.00334	0.533**	0.793**	0.548**	0.366***	1.240	0.282***
	(0.196)	(0.673)	(0.00276)	(0.195)	(0.275)	(0.202)	(0.100)	(0.634)	(0.0727)
Other higher degree × ICT	0.540*	1.759*	0.00711*	0.494*	0.975**	0.831**	0.153	-0.00127	0.0784
	(0.240)	(0.696)	(0.00334)	(0.238)	(0.309)	(0.257)	(0.124)	(0.553)	(0.0837)
A-Level etc × ICT	0.580**	1.513*	0.00653*	0.538**	1.078***	0.579**	0.295**	0.384	0.137
	(0.193)	(0.592)	(0.00300)	(0.190)	(0.277)	(0.196)	(0.101)	(0.343)	(0.0754)
GCSE etc × ICT	-0.0288	0.917	0.000506	-0.0719	0.428	0.158	0.166	-0.948*	0.203*
	(0.191)	(0.657)	(0.00296)	(0.188)	(0.253)	(0.177)	(0.109)	(0.389)	(0.0791)
Other Qualification × ICT	-0.358	1.468	-0.00432	-0.457	-0.240	-0.344	0.0478	-0.670	-0.107
	(0.268)	(0.996)	(0.00566)	(0.276)	(0.328)	(0.265)	(0.142)	(0.533)	(0.108)
No Qualification × ICT	-0.601*	0.443	-0.00163	-0.575*	-0.638	-0.278	-0.225	-1.062	-0.247*
	(0.278)	(1.073)	(0.00422)	(0.278)	(0.347)	(0.271)	(0.160)	(0.819)	(0.110)
Degree	-7.420***	-8.232**	-5.513**	-7.281***	-7.551***	-6.832***	-5.144**	-20.95***	8.362***
	(1.937)	(3.102)	(1.836)	(1.939)	(1.989)	(1.907)	(1.607)	(5.703)	(0.440)
Other higher degree	-5.326**	-5.324	-4.087*	-5.380**	-6.157**	-8.448***	-3.591*	-8.627	11.21***
	(2.053)	(3.238)	(1.881)	(2.044)	(2.121)	(2.090)	(1.680)	(6.362)	(0.485)
A-Level etc	-6.227***	-5.190	-4.822**	-6.208***	-7.259***	-7.810***	-4.711**	-7.653	9.361***
	(1.786)	(2.763)	(1.675)	(1.796)	(1.839)	(1.698)	(1.488)	(4.018)	(0.431)
GCSE etc	-3.577*	-3.018	-3.093	-3.582*	-4.545*	-5.510***	-3.834**	-0.402	7.040***
	(1.744)	(2.822)	(1.648)	(1.753)	(1.791)	(1.660)	(1.427)	(4.325)	(0.428)
Other Qualification	-0.00495	-1.629	0.462	0.270	-0.154	-1.442	-0.641	1.448	4.148***
	(1.703)	(2.942)	(1.447)	(1.693)	(1.749)	(1.593)	(1.297)	(5.503)	(0.522)
Age	0.383	0.354	0.631**	0.584*	0.386	-0.0277	0.238	0.814	0.144**
	(0.226)	(0.232)	(0.230)	(0.230)	(0.227)	(0.241)	(0.208)	(0.572)	(0.0480)
Age × Age	-0.00330*	-0.00276	-0.00356*	-0.00313	-0.00301	-0.00443*	-0.00149	-0.00531	0.00278***
	(0.00163)	(0.00170)	(0.00163)	(0.00163)	(0.00164)	(0.00178)	(0.00139)	(0.00419)	(0.000596)
Imports								0.0164	
								(0.0277)	
Dummy=1 if person identifies as female									-0.116
									(0.192)
Constant	11.99	10.43	4.270	6.185	11.75	25.44**	11.35	-1.467	11.10***
	(7.639)	(8.107)	(7.866)	(7.887)	(7.696)	(8.726)	(6.824)	(17.59)	(1.474)
Individual*Industry FE	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	221050	215784	221050	221050	218065	189046	219758	34586	221050

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 SI0.7: 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	-0.203	0.324	-0.00242	-0.210	-0.0700	-0.120	-0.185	-0.921	-0.441***
	(0.214)	(0.529)	(0.00350)	(0.213)	(0.281)	(0.223)	(0.103)	(0.849)	(0.0802)
Other higher degree × ICT	-0.124	0.272	-0.00102	-0.125	-0.183	-0.231	0.0584	-0.682	-0.218*
	(0.237)	(0.666)	(0.00415)	(0.240)	(0.321)	(0.321)	(0.117)	(0.434)	(0.0910)
A-Level etc × ICT	-0.229	-0.550	-0.00402	-0.213	-0.459	-0.260	-0.207	-0.279	-0.399***
	(0.191)	(0.532)	(0.00414)	(0.190)	(0.275)	(0.211)	(0.109)	(0.583)	(0.0826)
GCSE etc × ICT	-0.206	0.464	-0.00433	-0.193	-0.500	-0.268	-0.208	0.609	-0.576***
	(0.188)	(0.599)	(0.00422)	(0.188)	(0.267)	(0.186)	(0.114)	(0.569)	(0.0885)
Other Qualification × ICT	-0.473	0.451	-0.00512	-0.455	-0.767	-0.282	0.0199	0.722	-0.276*
	(0.345)	(0.976)	(0.00726)	(0.343)	(0.406)	(0.341)	(0.168)	(0.707)	(0.121)
No Qualification × ICT	0.402	0.216	-0.00628	0.357	0.297	-0.0357	0.196	0.564	-0.0417
	(0.391)	(1.761)	(0.00393)	(0.389)	(0.513)	(0.469)	(0.217)	(0.550)	(0.148)
Degree	2.319	0.601	0.480	2.000	1.350	0.598	2.550	5.599	0.188
	(2.371)	(4.350)	(2.182)	(2.370)	(2.469)	(2.576)	(2.094)	(6.375)	(0.577)
Other higher degree	0.522	-0.803	-1.018	0.424	0.271	-2.260	-0.756	1.857	-4.898***
	(2.439)	(4.405)	(2.214)	(2.444)	(2.553)	(2.721)	(2.160)	(5.875)	(0.612)
A-Level etc	0.879	1.462	-0.819	0.547	0.875	-0.927	0.560	-1.041	-3.063***
	(2.164)	(4.044)	(1.990)	(2.171)	(2.265)	(2.409)	(1.979)	(5.189)	(0.562)
GCSE etc	1.581	-0.428	0.0660	1.358	1.747	-1.159	0.780	-2.184	-3.539***
	(2.028)	(3.919)	(1.895)	(2.033)	(2.128)	(2.253)	(1.849)	(4.682)	(0.559)
Other Qualification	-0.495	-3.125	-2.565	-0.649	-0.0227	-0.994	-1.093	-5.388	-4.708***
	(1.824)	(3.600)	(1.548)	(1.824)	(1.898)	(2.012)	(1.506)	(4.562)	(0.657)
Age	0.128	0.189	0.0542	0.0739	0.0993	0.477	0.142	-0.681	0.538***
	(0.268)	(0.274)	(0.272)	(0.272)	(0.269)	(0.291)	(0.249)	(0.685)	(0.0545)
Age × Age	-0.00453*	-0.00531**	-0.00431*	-0.00447*	-0.00458*	-0.000146	-0.00475**	0.00234	-0.00612***
	(0.00182)	(0.00191)	(0.00180)	(0.00181)	(0.00183)	(0.00198)	(0.00158)	(0.00436)	(0.000664)
Imports								-0.0236	
								(0.0353)	
Dummy=1 if person identifies as female									-1.569***
									(0.215)
Constant	59.78***	59.35***	64.57***	62.59***	61.05***	35.24***	58.44***	71.52***	39.24***
	(9.050)	(10.02)	(9.628)	(9.694)	(9.120)	(9.902)	(8.238)	(21.46)	(1.598)
Individual*Industry FE	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	221050	215784	221050	221050	218065	189046	219758	34586	221050

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 SI0.8: 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	1.527***	2.877*	0.0130	1.415***	2.493***	1.220***	0.955***	0.446	0.871***
	(0.336)	(1.444)	(0.00733)	(0.324)	(0.499)	(0.363)	(0.172)	(0.809)	(0.0834)
Other higher degree × ICT	1.245*	2.365*	0.0109	1.230**	2.342***	1.293*	0.835***	0.404	0.752***
	(0.514)	(1.183)	(0.00610)	(0.468)	(0.602)	(0.553)	(0.218)	(1.107)	(0.0942)
A-Level etc × ICT	1.333***	2.683**	0.00374	1.259***	2.155***	1.065**	0.844***	-0.627	0.739***
	(0.355)	(0.943)	(0.00568)	(0.331)	(0.440)	(0.395)	(0.189)	(0.798)	(0.0855)
GCSE etc × ICT	0.657*	2.034*	0.000193	0.605*	1.214*	0.857**	0.505**	-0.186	0.555***
	(0.298)	(0.952)	(0.00594)	(0.285)	(0.475)	(0.330)	(0.181)	(0.614)	(0.0908)
Other Qualification × ICT	-0.251	2.645	-0.0150	-0.537	-0.149	-0.352	0.701**	-1.385	0.572***
	(0.534)	(1.776)	(0.00839)	(0.544)	(0.651)	(0.538)	(0.254)	(1.228)	(0.121)
No Qualification × ICT	-0.207	0.556	-0.0225*	-0.306	-0.0166	-0.179	0.544	-0.210	0.155
	(0.567)	(2.139)	(0.0104)	(0.571)	(0.753)	(0.609)	(0.294)	(0.812)	(0.145)
Degree	-12.11***	-12.67*	-11.48***	-11.11**	-13.70***	-12.69***	-10.51***	-20.47*	5.279***
	(3.591)	(6.093)	(3.255)	(3.493)	(3.803)	(3.826)	(3.036)	(8.923)	(0.569)
Other higher degree	-9.677*	-10.15	-9.504**	-8.994*	-11.61**	-14.59***	-8.767**	-22.55*	3.555***
	(3.982)	(5.948)	(3.469)	(3.810)	(4.134)	(4.239)	(3.295)	(10.44)	(0.609)
A-Level etc	-9.460**	-10.63*	-8.815**	-9.015**	-10.80**	-11.58***	-8.770**	-8.456	1.999***
	(3.136)	(5.152)	(2.850)	(3.047)	(3.287)	(3.287)	(2.776)	(7.123)	(0.556)
GCSE etc	-9.527**	-10.57*	-10.13***	-9.276**	-10.23**	-14.04***	-9.810***	-16.11*	0.328
	(3.147)	(5.089)	(2.842)	(3.039)	(3.339)	(3.315)	(2.742)	(6.586)	(0.553)
Other Qualification	-1.458	-6.587	-3.347	-1.282	-0.883	-2.890	-3.239	2.393	-1.624*
	(2.602)	(4.909)	(2.277)	(2.581)	(2.707)	(2.869)	(2.183)	(6.474)	(0.653)
Age	-0.730	-0.739	-0.347	-0.464	-0.835*	-1.305**	-1.051**	-1.263	0.392***
	(0.409)	(0.417)	(0.408)	(0.408)	(0.411)	(0.451)	(0.389)	(1.022)	(0.0548)
Age × Age	-0.000287	0.000314	-0.000818	0.000190	0.000587	0.00340	0.000328	-0.000378	-0.00193**
	(0.00317)	(0.00325)	(0.00308)	(0.00309)	(0.00318)	(0.00356)	(0.00279)	(0.00818)	(0.000673)
Imports								-0.139	
								(0.0773)	
Dummy=1 if person identifies as female									0.420
									(0.216)
Constant	81.14***	80.49***	86.36***	87.13***	83.87***	88.14***	91.61***	87.08**	33.27***
	(13.30)	(14.29)	(14.31)	(14.37)	(13.43)	(14.28)	(12.85)	(28.61)	(1.662)
Individual*Industry FE	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	221050	215784	221050	221050	218065	189046	219758	34586	221050

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.4.6 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 SI0.9 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 SI0.9: Predictors of attrition

	Leave sample		Change industry	
	(1)	(2)	(3)	(4)
ICT	-0.000605**		0.000164	
	(0.000208)		(0.000207)	
Degree × ICT		-0.00130		0.000943
		(0.00193)		(0.00181)
Other higher degree × ICT		0.00241		-0.000600
		(0.00219)		(0.00205)
A-Level etc × ICT		0.00182		0.000965
		(0.00174)		(0.00159)
GCSE etc × ICT		0.00344		0.00158
		(0.00184)		(0.00147)
Other Qualification × ICT		0.00134		-0.000813
		(0.00314)		(0.00345)
No Qualification × ICT		0.00650		0.00794
		(0.00388)		(0.00411)
Degree		0.0994***		0.0524*
		(0.0224)		(0.0248)
Other higher degree		0.0986***		0.0308
		(0.0237)		(0.0245)
A-Level etc		0.0643**		0.000180
		(0.0197)		(0.0216)
GCSE etc		0.0437*		0.00100
		(0.0200)		(0.0211)
Other Qualification		0.0393*		0.0172
		(0.0179)		(0.0197)
Age		0.0395***		-0.0225***
		(0.00372)		(0.00290)
Age × Age		-0.000163***		0.000143***
		(0.0000182)		(0.0000182)
Constant	0.0833***	-1.077***	0.275***	0.639***
	(0.00632)	(0.113)	(0.00813)	(0.0954)
Id*Ind FE	X	X	X	X
Year FE	X	X	X	X
Region	X	X	X	X
Observations	234662	234662	200579	200579

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.4.7 Alternative Clustering

Table SI0.10 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 SI0.10: 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	0.343***	0.0129	0.635*	0.589***	-0.203	1.527***
	(0.0359)	(0.0875)	(0.247)	(0.173)	(0.166)	(0.365)
Other higher degree × ICT	0.184***	0.00620	0.305	0.540**	-0.124	1.245***
	(0.0299)	(0.0777)	(0.333)	(0.199)	(0.203)	(0.330)
A-Level etc × ICT	0.0514**	0.168*	0.691*	0.580***	-0.229	1.333***
	(0.0172)	(0.0690)	(0.272)	(0.169)	(0.163)	(0.341)
GCSE etc × ICT	-0.0114	0.183*	0.211	-0.0288	-0.206	0.657*
	(0.0162)	(0.0827)	(0.295)	(0.188)	(0.173)	(0.278)
Other Qualification × ICT	-0.135***	0.0451	-0.951	-0.358	-0.473	-0.251
	(0.0262)	(0.0989)	(0.603)	(0.247)	(0.342)	(0.415)
No Qualification × ICT	-0.185***	0.227*	0.148	-0.601**	0.402	-0.207
	(0.0372)	(0.0998)	(0.497)	(0.227)	(0.316)	(0.474)
Degree	-1.995***	0.883	-0.617	-7.420***	2.319	-12.11***
	(0.247)	(0.846)	(3.446)	(1.861)	(2.173)	(2.964)
Other higher degree	-2.028***	1.446	-2.424	-5.326**	0.522	-9.677**
	(0.216)	(0.822)	(3.864)	(2.022)	(2.283)	(3.334)
A-Level etc	-1.628***	0.607	-5.519	-6.227***	0.879	-9.460***
	(0.145)	(0.720)	(3.017)	(1.691)	(2.033)	(2.546)
GCSE etc	-1.141***	0.773	-4.484	-3.577*	1.581	-9.527***
	(0.116)	(0.670)	(2.959)	(1.736)	(2.071)	(2.767)
Other Qualification	-0.441***	1.124	0.548	-0.00495	-0.495	-1.458
	(0.110)	(0.716)	(2.521)	(1.469)	(1.710)	(2.186)
Age	0.345***	-0.435***	-1.143**	0.383	0.128	-0.730*
	(0.0262)	(0.102)	(0.408)	(0.219)	(0.282)	(0.362)
Age × Age	-0.00312***	0.00158*	-0.00913**	-0.00330*	-0.00453**	-0.000287
	(0.000195)	(0.000699)	(0.00281)	(0.00155)	(0.00171)	(0.00223)
Constant	-2.821***	13.76***	133.1***	11.99	59.78***	81.14***
	(0.787)	(3.594)	(13.59)	(6.961)	(8.775)	(11.53)
Individual*Industry FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X
Region FE	X	X	X	X	X	X
Observations	179477	216130	103739	221050	221050	221050

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.4.8 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 SI0.11 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 SI0.11: All Outcomes Excluding Foreign-Born Workers

	(1) Hourly wage	(2) Unemployed	(3) Turnout	(4) Conservative	(5) Labour	(6) Incumbent	(7) UKIP
Degree × ICT	0.342***	0.0135	0.624*	0.585**	-0.206	1.535***	-0.428
	(0.0327)	(0.0723)	(0.282)	(0.197)	(0.216)	(0.339)	(0.345)
Other higher degree × ICT	0.185***	-0.000835	0.309	0.524*	-0.116	1.245*	-0.251
	(0.0338)	(0.0661)	(0.367)	(0.241)	(0.238)	(0.517)	(1.026)
A-Level etc × ICT	0.0497*	0.167**	0.687**	0.561**	-0.244	1.305***	-0.924*
	(0.0230)	(0.0624)	(0.264)	(0.193)	(0.192)	(0.356)	(0.469)
GCSE etc × ICT	-0.0123	0.178*	0.215	-0.0175	-0.232	0.679*	0.170
	(0.0186)	(0.0697)	(0.231)	(0.192)	(0.189)	(0.298)	(0.670)
Other Qualification × ICT	-0.138***	0.0357	-0.932	-0.307	-0.531	-0.275	-1.525
	(0.0289)	(0.0820)	(0.578)	(0.264)	(0.350)	(0.542)	(1.199)
No Qualification × ICT	-0.186***	0.237*	0.152	-0.549*	0.340	-0.140	2.845*
	(0.0400)	(0.106)	(0.470)	(0.276)	(0.392)	(0.569)	(1.431)
Degree	-1.998***	0.811	-0.531	-7.260***	2.072	-12.31***	13.22
	(0.212)	(0.820)	(3.345)	(1.959)	(2.397)	(3.644)	(7.029)
Other higher degree	-2.071***	1.479	-2.394	-5.299*	0.416	-9.937*	9.767
	(0.221)	(0.804)	(4.063)	(2.071)	(2.470)	(4.042)	(7.266)
A-Level etc	-1.637***	0.562	-5.441	-6.167***	0.565	-9.644**	9.401
	(0.157)	(0.714)	(2.852)	(1.801)	(2.189)	(3.176)	(6.711)
GCSE etc	-1.139***	0.713	-4.447	-3.761*	1.487	-9.933**	8.603
	(0.148)	(0.680)	(2.891)	(1.767)	(2.047)	(3.195)	(7.128)
Other Qualification	-0.435**	1.049	0.553	-0.363	-0.726	-1.750	17.05*
	(0.139)	(0.671)	(2.286)	(1.725)	(1.849)	(2.644)	(7.698)
Age	0.352***	-0.419***	-1.146**	0.408	0.0934	-0.826*	0.292
	(0.0273)	(0.0996)	(0.391)	(0.229)	(0.271)	(0.414)	(0.580)
Age × Age	-0.00312***	0.00153*	-0.00920***	-0.00323*	-0.00403*	0.000408	0.00596
	(0.000214)	(0.000607)	(0.00264)	(0.00164)	(0.00183)	(0.00320)	(0.00481)
Constant	-3.036***	13.43***	133.3***	11.43	60.36***	84.45***	-20.42
	(0.800)	(3.718)	(12.50)	(7.820)	(9.198)	(13.58)	(21.48)
Individual*Industry 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	174697	210773	103358	215730	215730	215730	53893

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.5 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 SI0.12: 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	-0.0846	-1.550**	-0.00298	-0.0825	-0.138	-0.0309	-0.0741	-0.676	0.146**
	(0.145)	(0.596)	(0.00212)	(0.145)	(0.226)	(0.174)	(0.0788)	(0.428)	(0.0550)
Other higher degree × ICT	-0.0506	-0.979	-0.00350	-0.0346	0.0478	-0.159	-0.134	-0.146	0.0763
	(0.207)	(0.662)	(0.00241)	(0.205)	(0.274)	(0.227)	(0.0926)	(0.422)	(0.0575)
A-Level etc × ICT	0.184	0.218	-0.00141	0.216	0.188	0.327*	-0.0794	0.222	0.181***
	(0.129)	(0.685)	(0.00195)	(0.130)	(0.186)	(0.136)	(0.0879)	(0.328)	(0.0545)
GCSE etc × ICT	0.0690	-0.836	-0.00363	0.0862	0.112	0.125	0.0420	-0.119	0.273***
	(0.133)	(0.441)	(0.00227)	(0.135)	(0.202)	(0.128)	(0.0840)	(0.523)	(0.0592)
Other Qualification × ICT	0.220	-0.540	0.00253	0.247	0.267	0.333	-0.0890	0.0991	0.181*
	(0.191)	(0.599)	(0.00428)	(0.189)	(0.239)	(0.254)	(0.150)	(0.382)	(0.0725)
No Qualification × ICT	0.259	0.158	0.00190	0.192	0.341	-0.00742	-0.00486	0.217	0.0705
	(0.244)	(0.826)	(0.00245)	(0.239)	(0.327)	(0.324)	(0.118)	(0.291)	(0.0754)
Degree	3.384*	6.710**	3.066*	3.401*	3.839*	1.602	3.363**	5.797	9.510***
	(1.476)	(2.386)	(1.286)	(1.472)	(1.570)	(1.609)	(1.268)	(3.418)	(0.335)
Other higher degree	3.034	4.961*	2.915*	2.989	3.091	1.142	3.007*	2.146	4.842***
	(1.615)	(2.523)	(1.409)	(1.609)	(1.680)	(1.776)	(1.399)	(4.166)	(0.351)
A-Level etc	2.452	1.490	2.767*	2.323	2.797*	0.793	3.700***	1.433	3.561***
	(1.255)	(2.136)	(1.096)	(1.246)	(1.320)	(1.356)	(1.113)	(2.367)	(0.306)
GCSE etc	1.272	3.057	1.445	1.140	1.581	0.725	1.955	0.106	1.546***
	(1.167)	(2.015)	(1.009)	(1.159)	(1.241)	(1.283)	(1.046)	(2.330)	(0.300)
Other Qualification	0.980	2.181	0.582	0.543	0.906	0.00199	1.533	3.396	0.716*
	(1.085)	(1.951)	(0.921)	(1.077)	(1.128)	(1.369)	(0.951)	(2.551)	(0.359)
Age	0.114	0.107	-0.0644	-0.0617	0.130	0.213	-0.0234	0.228	-0.244***
	(0.203)	(0.208)	(0.205)	(0.205)	(0.205)	(0.213)	(0.189)	(0.465)	(0.0349)
Age × Age	0.000904	0.00110	0.00116	0.00116	0.000838	0.000359	0.00159	-0.00381	0.00369***
	(0.00137)	(0.00142)	(0.00136)	(0.00137)	(0.00138)	(0.00151)	(0.00121)	(0.00300)	(0.000428)
Imports								0.00888	
								(0.0234)	
Dummy=1 if person identifies as female									0.928***
									(0.142)
Constant	-1.016	-1.146	3.405	3.125	-1.743	4.134	4.545	-12.04	7.774***
	(6.538)	(6.870)	(6.739)	(6.778)	(6.591)	(6.900)	(5.931)	(15.98)	(1.007)
Individual*Industry FE	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	221050	215784	221050	221050	218065	189046	219758	34586	221050

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table SI0.13: 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	-0.426	-1.374	0.0128	-0.344	-0.198	0.220	-0.264	-0.947	0.0917
	(0.344)	(1.494)	(0.0148)	(0.343)	(0.543)	(0.432)	(0.344)	(0.851)	(0.341)
Other higher degree × ICT	-0.249	-1.043	0.00984	-0.214	-0.617	-1.020	-0.0701	-0.578	0.176
	(1.026)	(2.196)	(0.0151)	(1.016)	(0.725)	(0.589)	(0.468)	(2.090)	(0.345)
A-Level etc × ICT	-0.922*	-1.926	0.00530	-0.847	-0.731	0.248	-0.389	-3.499	0.134
	(0.469)	(1.802)	(0.0137)	(0.468)	(0.581)	(0.367)	(0.348)	(2.238)	(0.345)
GCSE etc × ICT	0.173	-0.219	-0.00877	0.132	-0.224	0.691	-0.353	2.968	0.250
	(0.670)	(1.815)	(0.0175)	(0.668)	(0.735)	(0.402)	(0.399)	(2.040)	(0.350)
Other Qualification × ICT	-1.525	0.426	-0.0324	-1.539	-1.688	-1.835	-0.346	6.022	0.252
	(1.197)	(2.522)	(0.0262)	(1.198)	(1.301)	(1.054)	(0.509)	(3.761)	(0.362)
No Qualification × ICT	2.849*	6.805*	0.0845	2.947*	2.763	1.005	0.0681	20.66*	0.316
	(1.430)	(3.401)	(0.0496)	(1.430)	(1.478)	(0.717)	(0.625)	(10.00)	(0.373)
Degree	13.24	27.79*	8.957	13.02	11.98	6.343	0.885	105.0*	-2.749***
	(7.025)	(10.96)	(6.626)	(6.948)	(7.106)	(4.138)	(4.930)	(52.92)	(0.691)
Other higher degree	9.769	23.44*	6.560	9.910	10.08	11.54**	-1.048	87.51	-0.681
	(7.262)	(10.74)	(6.545)	(7.180)	(7.077)	(4.337)	(5.020)	(51.36)	(0.733)
A-Level etc	9.393	23.38*	4.075	9.245	8.727	8.134*	-1.275	89.48	0.506
	(6.707)	(10.49)	(6.269)	(6.631)	(6.766)	(3.874)	(4.722)	(50.07)	(0.719)
GCSE etc	8.586	20.63*	7.865	9.177	9.380	3.007	1.156	71.45	1.327
	(7.124)	(10.45)	(6.815)	(7.050)	(7.187)	(3.934)	(5.090)	(49.47)	(0.731)
Other Qualification	17.01*	23.77*	14.43*	17.48*	17.18*	8.085	4.201	67.47	1.652
	(7.686)	(10.61)	(7.017)	(7.574)	(7.801)	(4.869)	(5.616)	(47.77)	(0.881)
Age	0.273	0.283	0.239	0.255	0.198	-0.476	-0.149	3.394	-0.0123
	(0.578)	(0.582)	(0.581)	(0.579)	(0.582)	(0.478)	(0.558)	(2.016)	(0.0529)
Age × Age	0.00614	0.00634	0.00628	0.00611	0.00736	0.00766*	0.00845	-0.0187	0.000924
	(0.00480)	(0.00485)	(0.00482)	(0.00481)	(0.00480)	(0.00377)	(0.00454)	(0.0164)	(0.000655)
Imports								-0.0259	
								(0.0664)	
Dummy=1 if person identifies as female									-1.410***
									(0.192)
Constant	-19.97	-30.30	-18.27	-20.05	-18.70	-8.824	-2.980	-163.8	2.922
	(21.42)	(24.64)	(21.26)	(21.39)	(21.69)	(17.73)	(20.57)	(84.88)	(1.707)
Individual*Industry FE	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	54137	52995	54137	54137	53495	60141	53992	7103	54137

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. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

SI0.6 Mechanisms

SI0.6.1 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 SI0.14 provides an overview of their availability. Talbe SI0.15 gives basic descriptive statistics.

Table SI0.14: 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

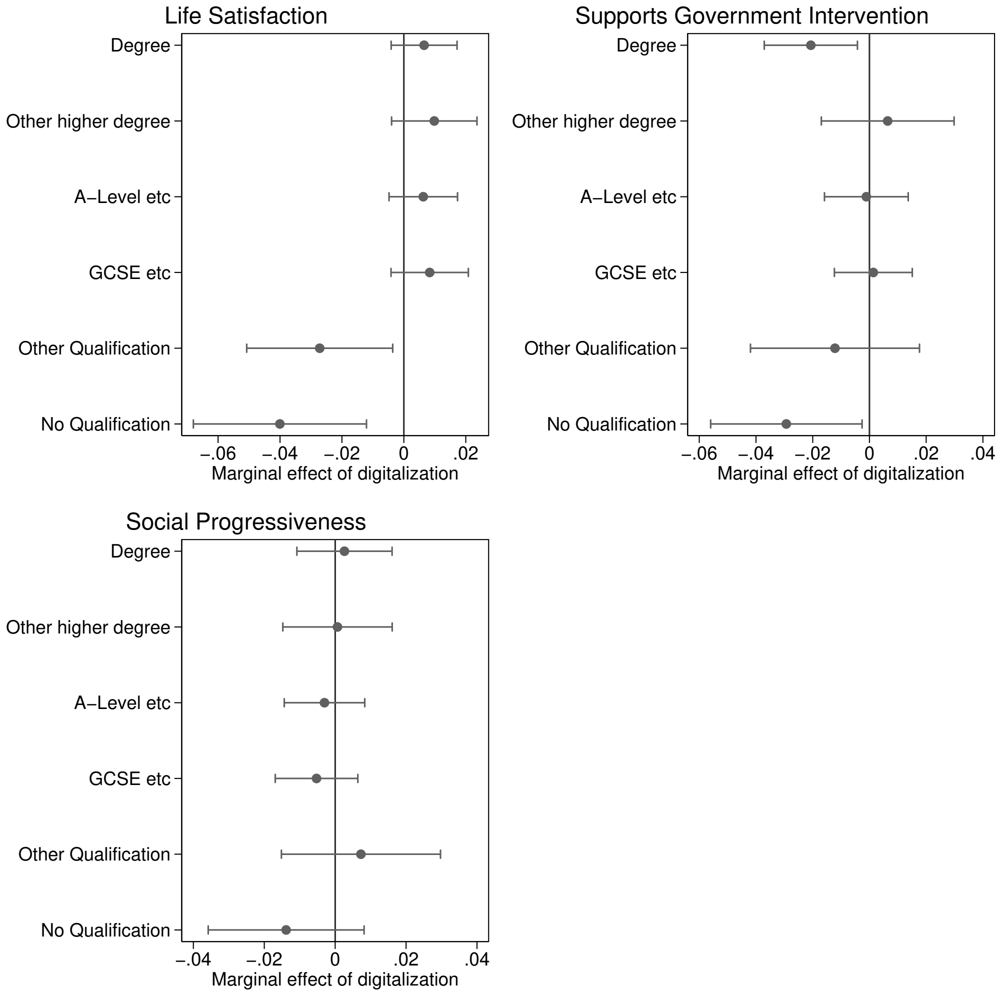
Table SI0.15: Mechanism Items: Descriptives

	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

SI0.6.2 Results

Figure SI0.7 presents the results of the analyses about mechanisms, which are discussed in the main text.

Figure SI0.7: Effect of digitalization on satisfaction and attitudes



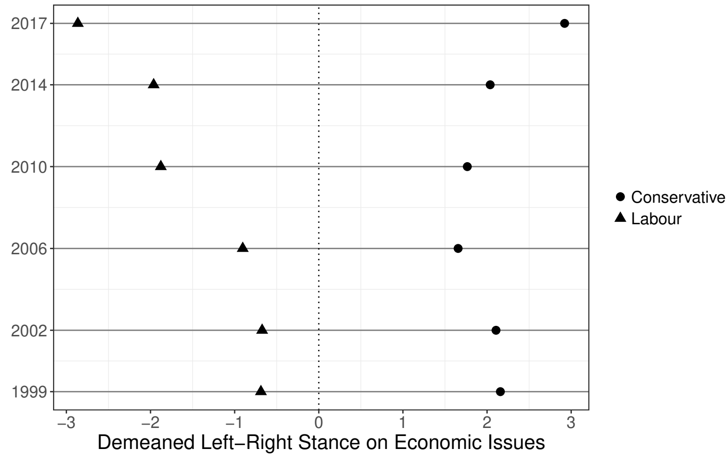
Note: Results show marginal effect of one unit increase in digitalization (1000 GBP in ICT capital/worker) on specified dependent variable, industry-spell fixed-effects specification.

SI0.7 Additional description of the UK political context

SI0.7.1 Positions of the parties over time

We use Chapell 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 SI0.8: Position on Redistributive Issues



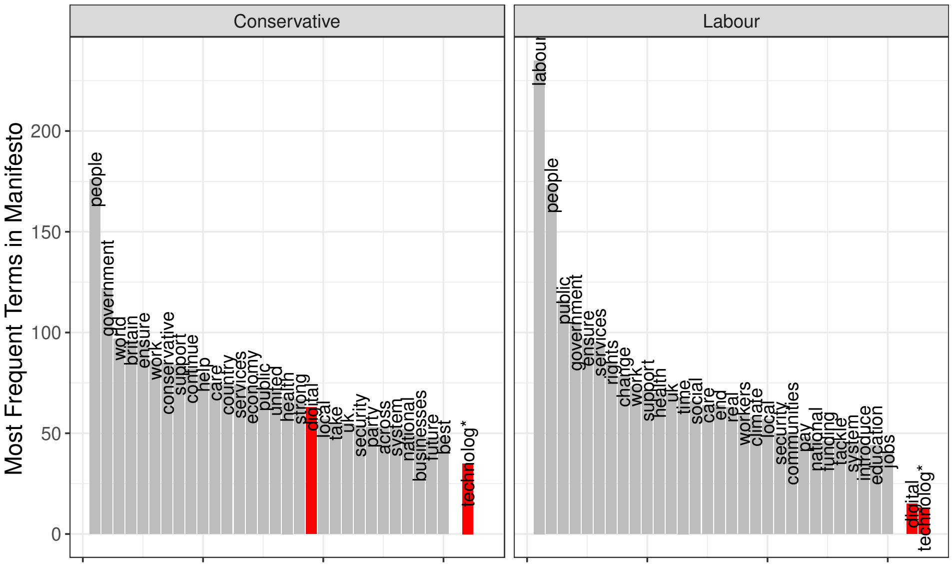
Source: Chapel Hill Expert Survey. Values of economic left-right position (lrecon) demeaned by year across all available party positions. Party positions weighted by vote share.

SI0.7.2 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 SI0.9 gives a broad overview and provides a comparison between the two parties.

Figure SI0.9: 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 SI0.16 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 SI0.16: Conservative Manifesto: Top Features among Keyword ('Digital') in Context

top features	count
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