ANNUAL REVIEWS

Annual Review of Political Science

Automation, Digitalization, and Artificial Intelligence in the Workplace: Implications for Political Behavior

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Annu. Rev. Political Sci. 2022. 25:463–84

First published as a Review in Advance on February 3, 2022

The *Annual Review of Political Science* is online at polisci.annualreviews.org

https://doi.org/10.1146/annurev-polisci-051120-104535

Keywords

technological change, voting behavior, political preferences, automation, artificial intelligence, AI

Abstract

New technologies have been a key driver of labor market change in recent decades. There are renewed concerns that technological developments in areas such as robotics and artificial intelligence will destroy jobs and create political upheaval. This article reviews the vibrant debate about the economic consequences of recent technological change and then discusses research about how digitalization may affect political participation, vote choice, and policy preferences. It is increasingly well established that routine workers have been the main losers of recent technological change and disproportionately support populist parties. However, at the same time, digitalization also creates a large group of economic winners who support the political status quo. The mechanisms connecting technology-related workplace risks to political behavior and policy demands are less well understood. Voters may fail to fully comprehend the relative importance of different causes of structural economic change and misattribute blame to other factors. We conclude with a list of pressing research questions.

INTRODUCTION

Automation, digitalization, and, more recently, artificial intelligence (AI) are fundamentally reshaping the employment structure of postindustrial societies. The introduction of computers, robotics, or the internet changes the way workers perform their jobs, modifies the value of skills, and creates entirely new job titles. This profound transformation is raising recurring concerns about the potential of labor markets to create sufficient employment and about the capacity of workers to acquire the skills needed to succeed in tomorrow's world of work. It should not come as a surprise that the strong distributive implications of introducing new technologies in the workplace have sparked a vivid academic debate about the political consequences of such transformation. More pessimistic views point to historical precedents in arguing that digitalization, automation, or AI pose a threat to democratic stability because citizens will revolt if economic modernization does not favor a large enough part of the population and states fail to sufficiently compensate those left behind. Other arguments, in contrast, highlight the role of technology as a unique source of innovation and prosperity, providing economic opportunity for many and thus shoring up support for twenty-first-century democracy.

This article attempts an overview of the state of the art in a very dynamic field. The most consistent finding of the literature is that those who lose out to technological innovation turn against the political status quo in general and toward the populist radical right in particular. In that sense, technological change is likely one of the forces contributing to recent political disruptions observed on both sides of the Atlantic. However, the disruptive potential of technological change is only one side of the coin. Technological change also creates a less conspicuous but numerically larger and politically highly relevant group of technology beneficiaries. The overall effects of these two processes on political outcomes and systems will depend on the magnitude of effects, the relative size of each group, the speed of change, and the potential for inclusion. In any case, the presence of an important but somewhat neglected group of "ordinary winners" (Gallego et al. 2022b) leads us to conclude that technological change might result in less electoral backlash than commonly assumed. Yet, it may be an important force in political realignments.

In a next step, we review work about the underlying mechanisms that link structural economic change and individual political behavior and discuss some unique features of automation and digitalization compared to international trade and immigration. Workers affected by technological change may not correctly attribute their economic decline to this transformation due to a combination of at least three factors: (*a*) the complexity and lack of visibility of this specific transformation, (*b*) basic psychological biases that make in-group–out-group conflicts a more compelling explanation, and (*c*) strategic mobilization by political entrepreneurs who downplay technology vis-à-vis other—politically more worthwhile—sources of structural change. Affected voters might misattribute their economic difficulties to related but distinct economic transformations, notably international trade and immigration. Recent survey evidence indeed points in this direction. This misattribution or diversion hypothesis can have important implications if it reduces demand for policies that address the downsides of technological change. If people misperceive the source of an economic problem, they are likely to support inadequate policies, which do not efficiently address the root of the problem. This channel may reinforce other possible channels by which economic decline affects second-dimension preferences on issues like immigration.

The brief preview of core arguments already hints at the thematic and conceptual contours of our review article. First, we do not aim at a comprehensive historical perspective but focus on the so-called Third and Fourth Industrial Revolutions, which include the developments of roughly the last 50 years. These stages of technological change were marked first by the rise of electronics, personal computers (PCs), and information technology (IT), and more recently also by robotics and data-based AI. We collectively label both waves as digitalization. Second, our key outcome of interest is political behavior broadly conceived. We mostly review implications for voting behavior and political preferences, and only in passing discuss the discourses of political parties and the policies that could moderate the impact of structural economic change. Third, we review the political consequences of digitalization and automation from a labor market perspective and limit our focus to the political downstream effects of technological change at the workplace.

Inevitably, these scope conditions neglect various closely related topics of similar importance. Perhaps the most important exclusion is that we take technological change as an independent variable and do not cover the large literature about why some countries and actors are more likely to develop and adopt new technologies than others. Taking technology as exogenous is a wild simplification, and it obviates that innovation is directed by both economic considerations and political struggles. Also, we concentrate on advanced industrial democracies, mostly the United States and European countries, and exclude autocracies. We discuss industrial relations only in passing and do not address the political influence of technological firms, nor the specificities of work performed through the platform economy. We examine how technological change affects citizens as workers and not as consumers (for example, of services provided by the gig economy or of news).

The remainder of this review is structured as follows. We first summarize the vibrant literature on the economic consequences of technological change and workplace automation from the perspective of attentive outsiders. Our goal is not to provide a detailed summary of this technically complex and rapidly evolving literature but instead to distill a few key insights about the distributive implications of technological change that in turn inform our discussion of likely political consequences. We then critically discuss the evidence on the implications of digitalization for political behavior in advanced industrial democracies, including its effects on support for populism, vote choice, and policy preferences. We conclude our review with a list of important research questions that have not yet been extensively addressed by the existing body of work.

ECONOMIC IMPLICATIONS OF TECHNOLOGICAL CHANGE

Technological change periodically raises anxiety and hope. Some voices worry that the introduction of new technologies can displace large numbers of workers, increase inequality, and ultimately lead to political upheavals. Yet, many authors, including most economic historians, point out that technology has been the main driver of economic growth in the last three centuries (Mokyr 1998, 2017). The maturation and adoption of a set of computer-based technologies since the 1970s, and by robotics and AI more recently, have again revived this centuries-old debate (Ford 2015, West 2018, Boix 2019, Frank et al. 2019, Iversen & Soskice 2019, Busemeyer et al. 2022).

In this section, we first briefly summarize a few helpful insights from formal models about the labor market impact of new technologies, and later turn to empirical research about the economic impact of digitalization in the Third and Fourth Industrial Revolutions.

Is This Time Different? Theoretical Considerations from Labor Economics

Modern theoretical economic models emphasize that new technology can both complement and substitute labor (Autor et al. 2003, Acemoglu & Autor 2011). The distributive implications of technological change strongly depend on whether a particular technology predominantly substitutes or complements labor and on which type of worker is affected by the substitution or complementation. In principle, both higher- and less-skilled workers can be complemented or substituted by technology. For instance, weaving machines in the early phases of the Industrial Revolution and

Fordist technologies in the first half of the twentieth century complemented low-skilled workers and substituted specialized workers. Hence, the distributive consequences of the introduction of a new technology vary across specific technologies. There is now widespread agreement that the computer-based technologies introduced since the 1970s in the Third Industrial Revolution, including the use of personal computers in the workplace and the introduction of basic algorithms, tended to complement workers with high levels of education, while they mostly substituted workers who performed routine tasks. Because many routine workers were located in the middle of the income distribution, this substitution process has contributed to a hollowing of the middle class and increased income inequality.

More recent theoretical models further refine a task-based approach, in which tasks performed by workers within occupations are the relevant unit of analysis. This approach combines a focus on tasks with theoretical models of directed technological change in which new technology is endogenous to the cost of labor or other factors (Acemoglu & Restrepo 2018; see also Caselli & Manning 2019, Hémous & Olsen 2021). Acemoglu & Restrepo (2018) distinguish between two types of technological change: automation, which allows the substitution of capital for tasks previously performed by labor; and the creation of new tasks. The authors argue that economies are usually in a balanced growth trajectory because there are powerful self-correcting forces when they go off-path. For example, when automation increases too much, the cost of labor decreases, reducing incentives to continue automating while increasing incentives to create new tasks. This explains why massive technological unemployment has not occurred in the past. However, a technological innovation that makes automation easier than the creation of new tasks ("so-so" innovation) can in principle lead to lower employment and labor shares.

Theoretical models can support both optimistic and pessimistic predictions about the effects of technology on labor market outcomes depending on (*a*) the extent to which the productivity effects of technology offset substitution effects and (*b*) which type of worker is most affected. How computer-based technologies and more recent technologies such as robotics or AI reshape labor markets is ultimately an empirical issue. The following sections thus aim at summarizing the most important findings from a rich and rapidly growing empirical literature in labor economics.

Empirical Findings: Routine-Biased Technological Change

In a decades-long research effort, economist David Autor and his coauthors have advanced our understanding of the labor market implications of technological change. Autor et al. (1998) claimed that the diffusion of computers and related technologies made educated workers more productive and increased inequality. Building on the then standard "skill-biased technological change" hypothesis, their article argued that computer-based technologies complement educated workers but said little about who was being substituted. In a closer examination of what computers do, through a case study of the banking industry, Autor et al. (2002) observed that rule-based or routine tasks (of the type "if X, then Y") can be more easily computerized than other tasks due to the logic of basic programming and show how a new technology, the proof machine, changed the task composition of jobs by automating routine tasks.

This observation set the stage for the seminal Autor-Levy-Murnane model that articulated what became known as the routine-biased technological change (RBTC) hypothesis (Autor et al. 2003).[1] Computer-based technologies, in addition to complementing skilled workers (and hence increasing the numbers of high-paying jobs for educated workers and low-paying service jobs of

[1]The term was introduced by Goos et al. (2009).

those who cater to them), substitute for labor in routine tasks, which were typically performed in industrial, sales, or clerical middle-income occupations, traditionally accessible to non-college-educated men. As a result of both upskilling and substitution of routine workers, new technologies lead to a hollowing of the middle class and growing income inequality. To assess this hypothesis empirically, the authors created a measure of routine task intensity (RTI), or the share of routine tasks performed by workers in an industry (later also estimated at the occupation level) based on data from occupational dictionaries in the United States, which is still the standard measure of automation risk. In subsequent studies, Goos et al. (2009, 2014) find that the RBTC hypothesis applies to advanced industrial economies outside the United States as well.

There is agreement that RBTC is a key driver of job polarization and thus may also contribute to rising income inequality (e.g., Goos et al. 2009, 2014; Autor & Dorn 2013; Nolan et al. 2019; Hoffmann et al. 2020). By contrast, there is debate about whether computer-based technologies have increased unemployment (e.g., Autor 2015, Dorn 2016, Gregory et al. 2019). This more contested link to unemployment is due to several reasons. Although the number of workers in routine occupations is shrinking, productivity growth can create jobs in the industries undergoing change or in other sectors. It is also increasingly clear that computer-based automation increases nonparticipation rates (Jaimovich et al. 2020). A significant share of routine workers who lose their jobs exit the labor force rather than move to unemployment (Cortes et al. 2017, Kurer & Gallego 2019), which suggests the difficulties of retraining them. Trade unions seem to be accepting a compromise in which they choose to preserve wages for existing routine workers at the expense of the creation of new jobs. Using data from the United States, Parolin (2021) finds that in regions and industries with high unionization rates, occupations with a high RTI did not experience declines in earnings, but employment shares in those occupations fell more.

Yet, automation risk is no longer confined to traditional routine industrial jobs, as popular examples about AI-powered radiologists, driverless cars, or automated legal assistants illustrate (Brynjolfsson & McAfee 2014, Frank et al. 2019). This expansion has motivated researchers to find ways to assess occupational risk that are not dependent on the RTI measure. Frey & Osborne (2017) classify a sample of occupations as highly likely to disappear in the next 20 years based on current opinion about technological feasibility and then apply a machine learning algorithm to predict the risk of automation of 702 occupations. Arntz et al. (2017) and Nedelkoska & Quintini (2018) use OECD's Programme for the International Assessment of Adult Competencies (PIAAC) data, and Feng & Graetz (2020) use data on job-specific training and engineering complexity to propose variants of this basic approach to estimate *how much* an occupation is at automation risk (rather than coding jobs as at risk or not). This later thinking about the measurement of automation risk is consistent with the theoretical task-based approach.

Directly Measuring Technology Adoption: Information and Communication Technology and Robotics

Empirical studies are combining novel measures of actual technology adoption, rather than potential risk, with causal identification designs.[2] Prior studies used variables such as IT expenditure (Bloom et al. 2012), sector-specific investment in information and communication technologies

[2]Note that technical potential to automate may never be realized because of legal, cost-related, or other barriers. A more practical type of concern with RTI and other measures of risk, which is particularly relevant for comparativists, is that tasks performed in jobs are based on US occupational dictionaries that are updated only infrequently. Because the actual task content of a job title varies across contexts and time, this measure does not necessarily travel well.

(ICTs) (Michaels et al. 2014), or IT intensity measured as the number of computers (PCs plus laptops) per worker (Bloom et al. 2016). But the empirical study of the labor market effects of technology has really taken off with studies of the case of robots. In a study of 17 countries, Graetz & Michaels (2018, p. 753) use data about robot sales collected by the International Federation of Robotics in 25 industries, which classifies a machine as a robot if it is an "automatically controlled, reprogrammable, multipurpose manipulator, programmable in three or more axes." The authors find that the adoption of robots did not affect overall employment in an industry but reduced the share of low-skilled workers. Carbonero et al. (2020) extend the analyses to 43 countries and show that robots have a small negative effect on employment in developed countries, but a much larger negative effect in emerging economies.

Robot adoption country case studies allow examining who gets displaced, who benefits, and local labor market equilibrium effects. Acemoglu & Restrepo (2020) estimate for the United States that exposure to robots in a commuting zone (defined as a shift-share variable that interacts baseline industry shares in a commuting zone to the acquisition of industrial robots in an industry) led to significant reductions in both the number of jobs and real wages. Lerch (2020) complements this study by using microdata and finds that 6 out of 10 displaced workers exit the labor force. While younger displaced workers often go back to education, older workers who do not re-enter the labor force go on disability benefits or retire early. For the case of France, Acemoglu et al. (2020) find that firms that purchase robots increase employment, value added, and productivity, but the aggregate effect at the industry level is negative because firms that do not purchase robots contract, offsetting the gains. In a careful study of the German case, Dauth et al. (2021) show that robot exposure is associated with a reduction in manufacturing jobs, which is fully offset by the creation of new jobs in services. The main beneficiaries are managers and engineers. And while incumbent workers maintain their jobs when robots are adopted (although wages suffer), younger workers are not hired and change their occupational choices. Using firm-level data from Spain, Koch et al. (2021) find that better performing firms are more likely to adopt robots and that adoption generates large gains for these firms—a reduction in labor cost share and a net job creation of 10% in 10 years—but that these gains are dominated by job destruction in other firms.[3]

It is important to note that research about the important US case has been held back by the lack of administrative and firm-level data. The US Census Bureau has recently started including questions about robotics, AI, cloud hosting, and other technologies in firms surveys (see Seamans & Raj 2019, Zolas et al. 2020). A second remark is that robotic studies should be read as case studies of the automobile industry, where more than 70% of the robots tracked by the International Federation of Robotics are deployed (see also Krzywdzinski 2020). Given the specificities of this industry (e.g., in many countries it is strongly unionized and geographically concentrated), it is unclear to what extent the findings apply to other industries.

Recent Developments: Artificial Intelligence, Automation, and the Pandemic

AI comes second to robots in terms of attention in empirical research. AI is a general-purpose technology that is analytically distinct from previous digital technologies based on the basic programming logic of "if X, then Y." Computer software that uses AI relies on algorithms to find patterns in data, create models, and make predictions. It is inductive and probabilistic. Examples

[3]Humlum (2019) uses data from Denmark and estimates that industrial robots slightly increase average real wages but produce a concentrated decrease in real wages of production workers in manufacturing (and especially older workers). Dixon et al. (2021) show, using firm-level data from Canada, that robot adoption leads to increased employee turnover and increased employment within the firm.

of applications include natural language processing and speech recognition, self-driving cars, machine translation, and image recognition (Varian 2018).

Like other technologies, AI technologies can in principle both substitute and complement labor (Agrawal et al. 2019) and there is much interest in which effect prevails in practice. To investigate this, Acemoglu et al. (2020) code online job advertisements since 2010 as being in AI-related positions or not. They estimate if firms have workers exposed to AI by coding if the tasks described in the ads can be performed with AI at current capabilities. Relying on three measures of current AI capabilities [Felten et al.'s (2019) AI occupational impact measure, Brynjolfsson et al.'s (2018) Suitability for Machine Learning index, and Webb's (2020) AI exposure score], they find that exposed firms hired more AI workers but fewer workers overall, suggesting that AI is being adopted to substitute labor and that displacement effects clearly trump productivity and complementary effects within firms. At the industry or occupation level, by contrast, they do not find consistent effects on employment or wages.

Two further recent investigations that measure the adoption of specific automation technologies are worth mentioning. Bessen et al. (2019) measure automation through a survey question asking firms in the Netherlands if they had paid for third-party automation services provided by specialists. Spikes in investment reduced the average worker's wages by 10% in 5 years and increased their probability to separate from firms and to retire early, compared to workers in matched firms that automated later. The authors also find that workers in firms that automated in some period had *higher* wages than firms that never automated. Perhaps the most clearly optimistic result of the recent set of studies is provided by Mann & Püttmann (2021), who compute a new measure based on classifying all US patents between 1976 and 2014 as automation patents or nonautomation patents.[4] They estimate that adopting automation technologies had a positive effect on local employment, which is driven by the service sector.

Finally, the COVID-19 (coronavirus disease 2019) pandemic may have worked as a catalyst for yet another surge in the adoption of new technologies in the workplace (for an early review see Coombs 2020), raising many highly relevant research questions. Clearly, some sectors will be more affected than others, with automation accelerating more in sectors in which work cannot be conducted online and routine tasks abound (Blit 2020) or in sectors with particularly high uncertainty (Leduc & Liu 2020). Teleworking has also forced companies to adopt new software that allows work to be performed remotely, but it is still unclear what will be the effects on the productivity of workers and the organization of firms.

In our view, Baldwin's (2019) concept of "globotics" will be particularly relevant in the post-pandemic world: As firms have set up the technological and organizational infrastructure that allows working from home, competition between well-paid workers in developed countries and workers in emerging economies that accept lower wages is likely to intensify. The resulting increased competition for skilled jobs, together with the potential of AI applications to automate relatively skilled tasks, suggests that in the Fourth Industrial Revolution, technology-related risks are possibly spreading beyond routine workers to other types of workers, including skilled ones.

Take-Aways for Studying Political Implications of Technological Change

Even if the literature in labor economics is still evolving and some questions are still contested, we can extract three key take-aways that are particularly relevant when thinking about the consequences on political behavior. First, RBTC has been a main driver behind job polarization and,

[4]Buarque et al. (2020) present a data set of AI patents in Europe.

perhaps, income inequality in recent decades, but the effects on employment have been positive or neutral. This could change with the further rise of AI, a general-purpose technology that may be producing a net reduction in employment and may be moving risk up the skill ladder.

Second, empirical studies in labor economics suggest that a given technology (such as robots) can have different aggregate and distributive effects across countries. The differences indicate the importance of culture, policies, and labor market institutions in modulating how technology affects labor markets. Political science provides the theoretical toolkit to explain such cross-national variation and to derive relevant policy implications and thus has the potential to effectively contribute to this literature.

Third, the adoption of a new technology has complex ripple effects throughout economies. Reduced-form analyses, which zoom in on displaced workers or specific firms or industries, obtain different results than equilibrium analyses, which estimate community-wide effects. But even if a technology is beneficial on average, costs tend to be concentrated, and they have been worse for male, middle-skilled industrial workers in the last few decades and more pronounced in areas where affected industries are clustered. Such clustering of adverse effects is relevant when considering political reactions.

CONSEQUENCES OF WORKPLACE DIGITALIZATION FOR VOTING BEHAVIOR

We now turn to the main questions of the review: Does labor market disruption due to new digital technologies affect the political behavior of workers? If so, how?

Historical experience suggests that significant technological change in the workplace, like other deep economic transformations with strong distributive consequences, is likely to create political upheaval. Unless they were appropriately compensated, workers who lost out from the introduction of weaving machines in the First Industrial Revolution often demanded compensation through nonmarket mechanisms (Caprettini & Voth 2020). True, pure Luddite movements against the machines have been historically rare, but discontent does not need to manifest politically as an explicit movement against technology. For instance, technological change is widely acknowledged as one of the key structural economic transformations that triggered the political movements that culminated in World Wars I and II (Eichengreen 2018, Boix 2019).

The recent transformations of labor markets and workplaces due to the use of digital technologies have coincided in time with extensive political unrest. The literature about the rise of populism identifies economic change and insecurity as one of the contributing factors (e.g., Rodrik 2018, 2020; Colantone & Stanig 2019).[5] However, this large literature has rarely specifically focused on or attempted to measure technological change. Instead, analyses of the economic drivers of the rise of populism have tended to focus on related but distinct economic factors such as international trade and globalization (for reviews see Naoi 2020, Walter 2021), with extensive attention to how growing trade with China and rising immigration have impacted political behavior. This relative inattention to technology compared to immigration or trade is surprising in light of the general agreement in the economics literature that technological change is a more important source of job polarization than offshoring or competition from migrants (e.g., Goos et al. 2014).

Our review first summarizes the empirical work that assesses if and how new technologies at the workplace may shape political behavior before we return to the question of the distinctiveness of technological change vis-à-vis other structural economic transformations.

[5]The relative magnitude of the effects of economic factors is hotly debated (Margalit 2019, Berman 2021).

Political Implications of Digitalization: Economic Losers Turn Against the Political Status Quo

The larger part of the existing literature on the political consequences of technological change has focused on voters at the losing end. As the previous section has made clear, the negative economic consequences of the adoption of computer-based technologies are strongly concentrated among routine workers, who are mostly men in blue- and white-collar jobs in the middle of the income distribution such as industrial workers or clerks. RBTC disproportionately affects a group of voters who used to think about themselves as middle class and who have the means to carry their dissatisfaction into the political arena (Kurer & Palier 2019). There is mounting evidence that this is exactly what they are doing.

A rapidly growing empirical literature finds that losers of technological change are disproportionately represented among those who are turning against the political status quo. Gingrich (2019) uses International Social Survey data and finds that workers in occupations with high RTI are more likely to vote for the populist right and for the mainstream left. Im et al. (2019) show in a cross-sectional analysis covering Western Europe that a measure of occupational automation risk is associated with voting for right-wing populist parties among citizens who are "just about managing" financially. This effect is not observed for those who already find it difficult or very difficult to live on their current income. Similarly, a panel-data analysis by Kurer (2020) covering Germany, the United Kingdom, and Switzerland shows that routine workers who are strongly exposed to automation but still manage to cling to their threatened jobs are particularly likely to vote for right-wing populist parties. Also using panel data, Mitsch (2020) studies young risk-exposed voters in Germany, i.e., potential automation losers who are only at the beginning of their occupational career. Drawing on a specific measure that captures the substitution potential of an occupation based on current technological capabilites (see Dengler & Matthes 2018), his analysis provides further evidence for disproportionate support for the radical right among this specific constituency.

A connection between RTI and voting for populist parties is also supported by Milner (2021), who finds in both regional- and individual-level analyses that RTI is positively associated with populist voting; by Dal Bó et al. (2021) for the case of Sweden; and by cross-national studies that do not focus on technology but use RTI as a control variable (Gidron & Hall 2017, Guiso et al. 2018, Oesch & Rennwald 2018, Inglehart & Norris 2019).

This basic finding is confirmed by analyses about the impact of robotization on voting behavior using International Federation of Robotics data. Based on a regional-level analysis, Frey et al. (2018) document that support for Donald Trump in the 2016 US election was significantly higher in local labor markets more exposed to robotization. Caselli et al. (2021) document an increased vote share for the far right in Italian municipalities more exposed to robotization. Finally, Milner (2021) finds, in analyses using regional data, that robotization increases support for right-wing populist parties.

An innovative recent contribution by Anelli et al. (2021) provides further evidence for a link between automation risk and radical right support. They argue that measures of automation risk based on current occupation underestimate the true scale of the phenomenon because workers in ostensible low-risk jobs, e.g., in sales or services, might very well be canonical automation losers. Their existing jobs could be either due to direct replacement in previous employment or indirect replacement in the sense that labor market entrants may be unable from the start to find stable and better-paid jobs in a shrunk manufacturing sector. Combining preautomation probabilities of working in a given occupation with individual automation risk scores from Frey & Osborne (2017) and the pace of regional robotization, Anelli et al. (2021) compute a measure of individual exposure to automation that aims to capture such direct and indirect replacement distinct from current employment. Measured as such, individual vulnerability to industrial robot adoption increases support for the radical right across 13 Western European countries.

An open question is if digitalization can push displaced workers to abstention from voting. Kurer (2020) finds that routine workers who lose their job and actually end up unemployed tend to abstain from politics. Boix (2019) also argues that the information and communication technology (ICT) revolution has led to increasing voter abstention. However, the question of the conditions under which technological change increases voter abstention rather than support for populism has received little attention in empirical studies. This is also one of the main puzzles in the more general literature about the consequences of economic shocks for political behavior (Margalit 2019).

Can the political backlash of economic losers be prevented through compensatory policies? Gingrich (2019) provides the only careful comparative study that assesses if public policies aimed at palliating labor market risks for workers affected by deindustrialization and automation can help prevent political disillusionment and the turn to the radical right. She finds that workers highly exposed to automation as measured by RTI are not less likely to vote for populist parties in countries with more generous early retirement policies and in-kind spending, nor in countries with more protective labor market regulation. This is a concerning finding, as it suggests that compensating workers is not effective at preventing their turn to protest voting.

In summary, the first consistent finding of the literature is that the losers of technological change are voting against the political establishment. This finding seems to hold for RTI, robotization, and related measures of substitution risk; can be observed across different political and institutional contexts; and does not appear to be substantially mitigated by compensatory policies. One important qualification to this finding is that it might not apply equally to different subgroups of the population. Recent evidence in particular points to differences between women and men (see Aksoy et al. 2021, Müller 2021, Gingrich & Kuo 2022), but similar heterogeneity in susceptibility to automation as well as political reactions could be expected between groups of workers from different races, ethnicities, or generations.

Other Implications: Does the Political Behavior of Economic Winners Also Change?

Economic losers of workplace digitalization are a politically relevant group, but they are a minority of the population. The literature in economics emphasizes that, along with substitution effects that produce losers in routine and manufacturing jobs, new technologies have extensive complementary effects on labor. As a consequence, technological change creates economic opportunity and produces a large group of beneficiaries with little reason to revolt against the political status quo.

The transformative potential of innovation and technological progress is at the heart of a related literature describing the transition of our society into modern "knowledge economies." Several influential accounts of political change in advanced industrial economies discuss the benign consequences of educational expansion and the fact that a broad upper middle class enjoys economic growth, wealth, and opportunity (Boix 2019, Iversen & Soskice 2019). The loss of mid-skilled routine jobs has been compensated by the creation of new nonroutine and service sector jobs, often highly skilled, in a broad upskilling process. Although the inclusiveness of contemporary knowledge economies remains disputed (e.g., Unger 2019) because its gains have been "concentrated at the upper tail of the income distribution" (Iversen & Soskice 2019, p. 21), this transition has undoubtedly fueled economic opportunity for many.

Despite this influential body of work that paints a considerably optimistic picture of economic modernization, the voting behavior of the economic winners of digitalization has received little attention in the empirical literature. Prospect theory (Kahnemann & Tversky 1979) provides one possible explanation for this inattention, as we may expect that economic gains are less likely to have behavioral consequences, including on political behavior, than economic losses. Still, three recent pieces of work suggest that workplace digitalization also has consequences for the political behavior of economic winners.

First, Broockman et al. (2019) study the political preferences of tech entrepreneurs, a group of extraordinarily successful and hence politically influential beneficiaries of technological change. Based on an original survey, their study documents respondents' complicated relationship to left–right positions in contemporary US politics. On the one hand, tech entrepreneurs have traditional center-right attitudes regarding regulation and state intervention. On the other hand, they hold unusually pronounced progressive values on noneconomic issues. These cross-pressures result in lukewarm Democratic support and can result in pressure to modify the positions of the party in a broader realignment process.

More directly examining how exposure to technology affects political preferences, we (Gallego et al. 2022b) have combined longitudinal panel data from the United Kingdom and information about ICT investment at the industry level. In line with the expectations of the knowledge economy literature, we find that ordinary winners of technological change are clear-cut supporters of the political status quo in the United Kingdom. We document how the experience of moderate but gradual wage increases as a result of ICT investment in an industry results in increased voting for the incumbent party, especially when the center-right is in power. In addition, a recent working paper finds that governments' investment in higher education, which helps workers reap the benefits of technological change, might represent one important mechanism explaining the progovernment shift in partisan voting (Lastra-Anadón et al. 2020).

Finally, Schöll & Kurer (2021) draw on fine-grained local labor market data from Germany to study how technological change affects regional electorates. They do find the expected decline in manufacturing and routine jobs in regions with higher robot adoption or higher investment in ICT but show that this decline was more than compensated by employment growth in the service sector and cognitive nonroutine occupations. On balance, the net change in the regional composition of the electorate may actually favor parties from the New Left rather than antiestablishment forces because workers in occupations dominating the growing sectors typically hold more progressive political values (Kitschelt & Rehm 2014). To be sure, aggregate welfare gains at the regional level likely mask certain disruptive consequences of automation (see Anelli et al. 2021). But in thinking about the political consequences of technological change in general, such equilibrium effects appear as an important corrective to more specific studies on particularly exposed parts of the voting population.

TWO VIEWS ON MECHANISMS: EFFECTS ON POLITICAL PREFERENCES

The results reviewed above suggest that workplace digitalization matters for voting behavior, but how it exerts effects is less clear. The question about the underlying mechanisms linking technological innovation to electoral competition is related to a second issue lurking in this literature: Is there something special about workplace digitalization vis-à-vis other structural changes?

We argue in this section that not all structural economic changes are alike. Different economic transformations can have different political consequences depending on whether and how they are perceived by voters and politicized by political actors. The literature in labor economics reviewed above suggests that technological change is the most important structural driver of job polarization and, perhaps, income inequality in recent years and a direct cause of the relative economic decline of routine workers. Yet, economic losers do not seem to directly and explicitly blame technological change for their (relative) decline in economic well-being. Instead, they at least partly (mis)attribute this decline to related but distinct economic transformations, notably international trade and immigration. At the same time, economic winners do not realize that digital economies disproportionately reward people like them; they embrace meritocratic discourses to justify their fate (Sandel 2020).

If confirmed, the misattribution or diversion hypothesis[6] is relevant not only as a curiosity for study but also because it is likely to lead to harmful policy responses. If people misperceive the source of an economic problem, they are likely to support inadequate remedies, which do not target the root of the problem. Worse, these policies may be inefficient and damaging.

To build our argument, we first review what we label the classical political economy model, which expects that changes in material interests directly affect economic preferences. We then elaborate on the alternative misattribution or diversion model, which recognizes the relevance of other factors such as perceptions about the causes of economic decline, the attractiveness of different policies, and positions on second dimensions of political conflict beyond redistribution.

Classical Political Economy: Direct Path from Economic Risk to Political Preferences

A first view of why digitalization may affect voting behavior builds on the large literature about the relationship between labor market risks and political preferences (e.g., Meltzer & Richard 1981; Iversen & Soskice 2001; Moene & Wallerstein 2001; Rueda 2005; Rehm 2009, 2011; Emmenegger et al. 2012). In standard political economy, potential labor market risks or realized economic decline shape economic interest, which in turn shapes political preferences.

The literature on digitalization and political preferences has examined if automation risk affects preferences for redistribution and other economic attitudes. The evidence so far is mixed (for a thorough review, see Weisstanner 2021). Thewissen & Rueda (2019) regress RTI on attitudes toward redistribution in European Social Survey data and find a positive correlation. Kurer & Häusermann (2022) use a measure of subjective automation risk that asks workers in eight countries how likely it is that their job will be automated by a robot, software, AI, or another technology in the next 10 years as well as two measures of objective risk. They find that workers at higher risk support spending more on unemployment benefits, but not on pensions or other policies. Yet, other studies find no link between risk of digitalization and preferences for redistribution. Gallego et al. (2022a), using correlational and experimental analyses of data from Spain, find no correlation between several objective measures of automation risk and preferences for redistribution (though they find associations with other attitudes). Several experimental papers have provided information about automation risk and do not find that it affects preferences about welfare policies, immigration, or trade (Zhang 2019), or find that it only increases demand for redistribution if a politicized rhetoric that explicitly presents redistribution as an antidote to increasing inequality is also primed (Jeffrey 2020).

[6] The terms misattribution and diversion point at two different but possibly compatible processes. Using the term misattribution emphasizes micro-level psychological processes that may motivate people to assign blame for relative economic decline actually caused by technological change to other factors. Using the term diversion emphasizes the active role of political entrepreneurs who frame issues according to calculations about their mobilization potential.

Redistribution and social protection are not the only—and perhaps not the most adequate—policy response to technological change. However, the growing evidence about how automation risk affects preferences for more active kinds of social policy produces similarly inconclusive findings. Preferences about labor market policies are particularly relevant, as these are often advocated as an adequate response to the risks posed by automation. Both Busemeyer & Sahm (2021) and Weisstanner (2021), relying on RTI, and Kurer & Häusermann (2022), relying on a measure of subjective automation risk, find that at-risk workers do not support more spending on active labor market policies or education. At the same time, using data from the European Social Survey and several measures of risk, Im (2020) reports that workers at high risk of automation are more likely to demand active labor market policies.

Other work has examined how digitalization risk affects preferences for a universal basic income, an unconditional cash transfer with no conditions for receipt nor time limits. A universal basic income is presented by advocates as a policy that can help reduce risks in a context of rapid technological innovation (e.g., Van Parijs 2004). Sacchi et al. (2020) find that RTI is correlated with support for a universal basic income among some subgroups of voters in Italy. However, Dermont & Weisstanner (2020), Weisstanner (2021), and Busemeyer & Sahm (2021), using data from the European Social Survey, do not find that higher risk of automation is correlated with demand for a universal basic income.

This literature provides mixed results on whether exposure to automation-related risks affects the economic preferences of workers. The mixed findings may be due to the fact that different studies use different measures and model specifications, and some agreement on these two aspects is crucial to move forward. They can also be due to genuine differences across contexts, as pointed out by Weisstanner (2021); for instance, in some countries workers may be more aware of automation risk than in others, or they may feel more protected by the state. Another source of variation may be in the political discourse about digitalization, which varies across countries, although in general "[c]entral political actors have used their discursive agency to frame digitalization not as something that should be cushioned by compensatory policies but as something that can and should be actively shaped" (Marenco & Seidl 2021, p. 403).

To be clear, we do not generally discard preferences on economic policies as a mechanism linking technological change to vote choice, and we have claimed in our own work that the economic effects of digitalization may affect preferences about economic policies (Gallego et al. 2022b). But we note that the existing evidence is just not as robust as in the case of the correlation between technological change and voting. The evidence possibly points at partial misattribution of determinants as well as at relevant between-country variation.

Alternative Channels Linking Risk and Preferences: Misattribution and Diversion

An alternative theoretical narrative in this literature starts with the widely accepted fact that routine workers perceive that (*a*) neither governments on the mainstream right nor those on the mainstream left have been able to stop their secular economic decline and (*b*) governments have neither descriptively nor substantively represented their views. Since the early 1980s, working-class politicians in general and routine workers in particular have disappeared from political parties (O'Grady 2019, Dal Bó et al. 2021). However, this is not an apathetic or disengaged group, and they still participate in politics but turn against establishment parties. The simplest version of this argument is that economic decline motivates affected workers to support political outsiders as a form of protest. For instance, Frey et al. (2018) interpret their findings about how robotization increased support for Trump in the 2016 election as a sign of blind retrospection and protest voting.

Still, the specific platforms that digitalization losers end up supporting are puzzling. While migration and trade are central in the types of "economically nationalist" platforms (Colantone & Stanig 2019) offered by the populist parties to which digitalization losers turn, policies more directly related to technological change are not discussed often. As Rodrik (2018, p. 18) notes, "While disentangling the effects of automation and globalization is difficult, most existing studies attribute the bulk of the decline in U.S. manufacturing employment to the former rather than the latter. Yet we do not see populists campaign against technology or automation." In elections, digitalization generally remains a marginal issue with little visibility in party manifestos, but when it is discussed, most parties propose to speed up technology adoption (König & Wenzelburger 2019). Emerging related issues that may well become politicized more in the future are the gig economy, AI, and online commerce, although positions on these issues are not (yet) clearly correlated with existing cleavages, and how they are constructed varies across countries (Thelen 2018, Marenco & Seidl 2021).

We start with the plausible assumption that workers are unlikely to know the exact contribution of different causes to their relative economic decline and suggest that some causes are more appealing as explanations than others. For reasons further elaborated below, technological change may be a particularly intangible and inaccessible explanation and hence especially prone to misattributions. This does not imply that technological change does not matter for political behavior, but that discontent actually caused by this transformation is likely to manifest in the political arena, at least partially, through debate on other issues.

There are several candidate explanations of secular economic change, but three core structural economic possibilities are (*a*) international trade and globalization, (*b*) competition from immigrants, and (*c*) digitalization-related technological change. We have identified three possible reasons why technological change may feature less prominently in the political arena and political discourse than one would expect based on its paramount economic relevance.

First, it may be more psychologically gratifying to attribute economic decline to globalization. Immigration and trade offer clear out-groups to mobilize against (migrants, China), and there are relatively straightforward policies to counteract them (borders, tariffs). Technological change is different. Seeing one's tasks performed by machines can be particularly hard on self-esteem. It may be more difficult psychologically (and practically) to mobilize against nonhumans than against human out-groups. The policies adequate to meet this challenge, such as intensive and continuous retraining, may be costly and unappealing for workers. On the side of winners, meritocracy offers a psychologically attractive explanation of the good economic fortune of the highly educated in recent decades (Sandel 2020).

Second, and most likely as a consequence of the first reason, political entrepreneurs (especially populist parties) supply discourses against immigration and trade that connect economic grievances to policy solutions (Kriesi et al. 2008, Kurer & Palier 2019). Parties contribute to voters' misattributions by making some explanations more cognitively available than others. In other words, voters may develop certain policy opinions because politicians and parties cue or divert them into thinking that the cause of economic transformations that they experience as undesirable is international trade or immigration.

A third reason for the low political salience of technological change may be its subtlety. The speed and visibility of each structural change may affect how likely it is to become politicized. Politicization may be more likely when events occur as specific visible shocks because sudden shocks are more noticeable than ongoing processes. Identifiable events have occurred, for instance, in the liberalization of trade with China, and the refugee crisis has made the issue of immigration more salient in some countries. In the case of automation, the threat may be much more gradual than in the cases of international trade or immigration.

The most articulated account of the misattribution narrative has been provided by Wu (2021a,b), who shows that workers at higher risk of automation feel less secure in their jobs and are more likely to oppose free trade and immigration, but they do not have different preferences about spending on technology. Similarly, Kaihovaara & Im (2020) find that European workers in high-RTI occupations are more likely to support trade protectionism and restrictions on immigration. Further supporting this claim, Rodrik & di Tella (2020) show that in an experimental setting, citizens are more supportive of protectionism when they hear about workers who have lost their job due to technological change.

Ideas about misattribution and diversion are compatible with current debates about the intertwined economic and cultural origins of populism, which emphasize the interaction between relative economic decline, nationalist attitudes, and identity politics (Gidron & Hall 2020, Noury & Roland 2020, Berman 2021). Recent research finds that the discontent among historically dominant groups in economic decline manifests politically in forms that reach beyond the political left–right dimension typically at the center of traditional political economy models. If the workplace is no longer a reliable source of social status, voters who suffer from relative status decline may seek redress by adopting other identities. One important mechanism is that members of historically dominant groups develop authoritarian attitudes as a protection from social regression and identity loss stemming from long-run economic change, and they turn against groups perceived as inferior in order to preserve status (Gidron & Hall 2017, Ballard-Rosa et al. 2022). A second general mechanism is that when individuals experience a relative economic decline, their occupation-related identities become less valuable, and they become more likely to choose identities that can provide higher prestige and self-esteem, such as national identities (Shayo 2009).

The relative importance of the different channels through which structural economic change can affect political preferences (misattribution or diversion, authoritarian aggression, and social identity) remains unknown. Yet, the three channels point at the possibility that fundamentally economic processes like a changing employment structure can cause changes in noneconomic—or not purely economic—political preferences and identities if economic anxiety and concerns about a shifting status hierarchy are channeled into in-group identification and opposition against a tangible out-group rather than into arguments against abstract structural change related to technological innovation (Gidron & Hall 2017, Rodrik 2018, Kurer 2020).

More research is needed, but overall this stream of work suggests reasons why automation is different from other sources of economic decline. There are unique difficulties in organizing politically around this issue and connecting problems to solutions. At the individual level, it is not easy for voters to correctly establish the contribution of technological change versus other causes of structural change and to discern which policies are more likely to be helpful. At the meso level, political intermediaries such as parties and trade unions may find it difficult to mobilize voters around complex discourses about how technology affects the employment structure and to connect this structural change to specific policies. They may turn to simpler explanations revolving around out-groups instead. These difficulties have important implications—as wrong diagnoses will likely lead to misguided policy responses.

TAKING STOCK: WHAT WE KNOW AND WHAT WE NEED TO UNDERSTAND BETTER

It is now reasonably well established that digitalization creates economic losers who are more likely to vote against the political status quo, particularly from the populist right, but it also creates winners with distinct preferences who support the status quo and can even take over some existing political parties. Both processes are likely driving forces of the current political realignments observed across countries, in which right-wing parties are adopting more economically nationalistic policies while left-wing parties are emphasizing tolerance-related issues (Colantone & Stanig 2019, Iversen & Soskice 2019, Rodden 2019). But our reading of the literature is that technological change is not bound to create a large political backlash. Whether this occurs depends on the magnitude of effects, which are still not well understood, and the size of the population of directly affected economic losers, which until now has been a relatively small group numerically (although this may change with the widespread introduction of automation and AI in the aftermath of the COVID-19 pandemic).

It is unclear whether citizens at high risk of substitution demand the types of government intervention advocated by economists and policy experts to face this challenge. Citizens may have difficulty differentiating between different structural sources of change accurately or they may not like policy solutions that are individually costly for them, such as retraining. Despite the dominant role of technological change in reshaping labor markets, blame attribution for potential material hardship seems more strongly concentrated on international trade or immigration. By implication, political responses to technological change manifest indirectly rather than as a conscious and deliberate reaction to an either benign or detrimental exposure to new technology.

Based on these key insights of the existing literature, we conclude this review by highlighting seven areas in need of deeper attention to arrive at a more encompassing understanding of the politics of workplace automation.

Research Focus 1: Measurement and Research Design

The existing body of work in political behavior has mostly researched the implications of routineness and robotization, two concepts for which we have available empirical measures, and has relied heavily on cross-sectional surveys and regional data. However, technological change encompasses different and potentially more important aspects, such as AI. The field needs innovative approaches to measure the impact of the introduction of specific technologies. The field also lacks widespread agreement on basic specification issues such as the use of occupational controls. Moreover, economy-wide technological shock–like "treatments" comparable to the China shock for the case of trade are rare or nonexistent. Case studies that trace shocks in specific occupations or industries may be useful.

Research Focus 2: Gender, Race, Generations

Female occupational trajectories in increasingly automated and digitalized labor markets differ systematically from male trajectories but have hardly been studied so far. Little attention has been paid to the experiences of workers of different ethnicities and races. We also suspect that an intergenerational perspective is relevant. The implications of technological change are very different for workers approaching retirement than for new job entrants. Many jobs disappear over generations, and individual workers do not necessarily experience a technology shock within their work career, but the consequences might be felt strongly among the next generation. What happens to middle-class children who suddenly see the occupational trajectory of their parents in mid-pay, well-protected routine jobs blocked and either have to succeed in higher education or end up in low-pay and low-prestige jobs in the service sector?

Research Focus 3: Winners of Technological Change

The field would benefit from a more balanced view of both winners and losers of automation. Initial work has provided evidence that winners in the United States and the United Kingdom support mainstream parties, but in the United Kingdom, some winners seem to have shifted to the Conservatives (at least before the Brexit realignment) while in the United States, they are increasingly a core constituency of the Democrats. The behavior of winners in different political and institutional contexts deserves more attention. Also relevant is differentiation between the few individuals who have been the disproportionate winners of digitalization, such as successful tech entrepreneurs, from the large number of ordinary winners.

Research Focus 4: The Role of Political Parties

Despite all the public attention to the distributive implications of the Third and Fourth Industrial Revolutions, political parties have been surprisingly silent on this topic. When party manifestos or political speeches do address automation and digitalization, they tend to focus on abstract labor market opportunities in the future or, much more often, on more tangible issues like digital infrastructure, data protection, or the modernization of administrative processes rather than the potentially disruptive transformation of labor markets. So far, there are no discernible trends as to which party family is willing to claim competence in this important domain. Given the salience of the topic and the considerable size of the sociostructural groups of technology winners and losers—if we can define them as groups in the sociological sense—we cannot rule out that a more active politicization of the distributive implications of technological change might occur, and it will be interesting for researchers to systematically study how and by whom this initiative is taken.

Research Focus 5: Perceptions and Mechanisms

Much more work on individual perceptions of the upsides and downsides of technological change at the workplace is needed. The mechanisms linking structural change and individual political response are not well understood. Some initial evidence points at a largely indirect relationship. Voters might experience material change brought about by technology but attribute this experience to other structural factors such as international trade or immigration. What are the implications of such misattribution? Does it constitute a barrier to an efficient policy response? And to what extent do political actors systematically (mis)represent this attribution discourse to their benefit?

Research Focus 6: Comparative Work

The strong reliance on the US labor economics literature might mask important variation and hide potentially powerful political remedies already in place in some countries. There is a need for more explicitly comparative empirical work and theorizing, taking into account underlying variation in the labor market implications of structural change as well as variation in the institutional setting that may cushion its adverse effects. Differences in education and, particularly, vocational education and training regimes should have a more prominent role in this research agenda. In theorizing political responses to technological change, the findings of the important studies examining distributive implications in the US labor market cannot be blindly applied to other countries and world regions.

Research Focus 7: Policy Responses

The debate on efficient and feasible policy responses to accelerating technology-induced labor market transformation is still in its infancy. Existing policy-prescriptive work is very much tied to the classic toolbox of policy responses (minimum wages, unemployment benefits on the passive side, investment in education on the active side). The field would benefit from a more visionary policy typology that does justice to the magnitude of change and reaches beyond the existing set of standard responses. The ideal response to technological change is far from agreed upon.

Transformative change needs transformative ideas for the welfare state, including predistribution, new types of taxation, and concrete ideas for the practical implementation of life-long learning.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

We thank the editors and the anonymous reviewer for providing careful comments about the manuscript. We also thank Silja Häusermann, Reto Bürgisser, Henning Finseraas, Alex Kuo, Marius Buemeyer, Helen Milner, Vincent Pons, Peter Loewen, Annette Brown, and seminar participants at the Universitat de Barcelona, the University of Konstanz, and the working group on "Status in the Knowledge Economy" for providing comments on previous versions of this article. This review is part of the research Project "How Technological Chance Reshapes Politics: Technology, Elections and Policies" (TECHNO), funded by the NORFACE programme of the European Union (PCI2020-112198), the Spanish Agency of Research, and the Swiss National Science Foundation.

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Annual Review of Political Science

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Errata

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