Political machinery: did robots swing the 2016 US presidential election?*

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Abstract

Technological progress has created prosperity for mankind at large, yet it has always created winners and losers in the labour market. During the days of the British Industrial Revolution a sizeable share of the workforce was left worse off by almost any measure as it lost its jobs to technology. The result was a series of riots against machines. In similar fashion, robots have recently reduced employment and wages in US labour markets. Building on the intuition that voters who have lost out to technology are more likely to opt for radical political change, we examine if robots shaped the outcome of the 2016 US presidential election. Pitching technology against a host of alternative explanations, including offshoring and trade exposure, we document that the support for Donald Trump was significantly higher in local labour markets more exposed to the adoption of robots. A counterfactual analysis based on our estimates shows that Michigan, Pennsylvania, and Wisconsin would have swung in favour of Hillary Clinton if the exposure to robots had not increased in the immediate years leading up to the election, leaving the Democrats with a majority in the Electoral College.

JEL: J23, J24, J31, N60, O14

Keywords: automation, industrial revolution, labour markets, technological change, political economy

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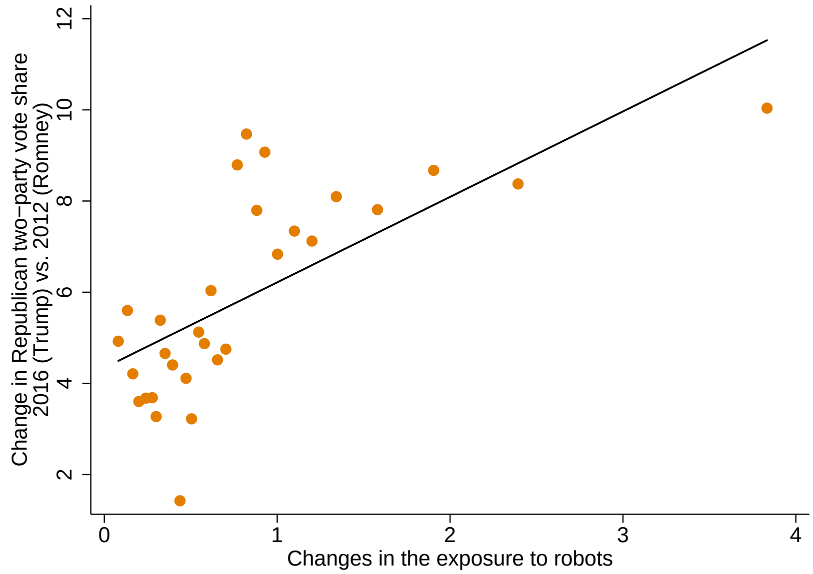
1 Introduction

Was the outcome of the 2016 US presidential election shaped by workers losing out to automation? According to a recent poll of unemployed Americans who were able to work, more than a third identified automation as a prime reason for their misfortunes (Hamel *et al.*, 2014). Moreover, a staggering 72 per cent of surveyed Americans fear a future in which computers and robots can do more human jobs, while 85 per cent favour policies to restrict the use of machines to hazardous jobs (Pew Research Center, 2017). Even though the causes of the populist backlash in America and Europe are far from conclusive, parallels have been drawn with the machinery riots of the British Industrial Revolution, when 'Luddites' smashed power looms in fear of losing their jobs. A post-election article in *The Wall Street Journal* featuring the headline 'Trump's focus on jobs, globalization and immigration tapped anxiety about technological change' speaks to the frequent belief that automation was a real cause of voter concern. Despite such beliefs, empirical efforts to examine the extent to which automation shaped the outcome of the US presidential election have remained scant. What is clear is that the vote for Donald Trump was a vote against the status quo: according to the exit polls, 82 per cent of voters believed that the Republican candidate would perform best in bringing about change, while the corresponding figure for Hillary Clinton was a meagre 14 per cent.

This paper examines the link between workers exposure to automation and voting patterns in the 2016 US presidential election through the lens of economic history. Our analysis builds on two sets of observations. First, technological change in the short to medium term is rarely a Pareto improvement: as automation has made inroads into a wider set of industries and occupations, it has left a sizeable fraction of the workforce worse off. In particular, the sharp reduction in middle-income jobs in the US economy cannot be explained without reference to the disappearance of 'routine jobs'—i.e. occupations mainly consisting of tasks following well-defined procedures that can easily be automated (Autor *et al.*, 2003; Acemoglu and Autor, 2011). As traditional middle-income jobs have dried up, many workers have shifted into low-income service occupations (Autor and Dorn, 2013), while others have dropped out of the workforce altogether (Cortes *et al.*, 2016a). According to Eberstadt's (2016) timely book, *Men Without Work*, 24 per cent of prime-aged men in the US will be out of work by 2050 at current trend. A prime explanation is the robot revolution, which has contributed to both joblessness and wage reductions, especially among American men (Acemoglu and Restrepo, 2017).

Second, the economics of automation cannot be separated from its politics. For ordinary workers, their skills constitute their capital; it is from their human capital that they derive their subsistence. Because automation is accompanied by creative destruction in employment, which often comes with social costs—including vanishing incomes, forced migration, skill obsolescence, and episodes of unemployment—it threatens not only the incomes of in-



Notes: This figure presents a non-parametric illustration of the county-level relationship between percentage point differences in the Republican two-party vote share between the 2016 and 2012 elections based on data reported in Dave Leip's *Atlas of US Presidential Elections* and changes in the exposure to robots between the immediate years prior to each election based on data from the International Federation of Robotics and the American Community Survey respectively, which we describe in more detail in the main text. To construct the figure, we sorted all observations into 30 equal-sized bins and plotted the mean change in the Republican two-party vote share versus the exposure to robots within each bin, while the line corresponds to a fitted OLS regression based on the underlying (ungrouped) data.

Figure 1: Exposure to robots and the vote for Trump

cumbent producers but also the power of incumbent political leaders (Acemoglu and Robinson, 2013). The reason is simple: if workers who have lost out to automation do not accept labour market outcomes, they will resist the force of technology through non-market mechanisms, such as political activism (Mokyr, 1990, 1998; Mokyr *et al.*, 2015). The British Industrial Revolution provides a case in point. The downfall of the domestic system—which was gradually displaced by the mechanized factory—inflicted substantial social costs on workers, leading them to rage against the machines that pioneers of industry marvelled about. The 1779 riots in Lancashire and the Luddite risings of 1811–13, are only two of many attempts to bring the spread of machines to halt (Mantoux, 2013). Although the Industrial Revolution began with the arrival of the factory, it ended not just with the construction of the railroads but also with the publication of the *Communist Manifest*o. While the accelerating pace of technological progress paved the way to modernity, it also bred many political revolutionaries along the way.

Against this background, we examine whether the increased adoption of robots caused American voters to opt for radical political change. A recent study by Acemoglu and Restrepo (2017) documents that the diffusion of robots across US labour markets has caused employment and wage reductions in particular among workers in blue-collar jobs without a college degree. Notably, these are precisely the voter groups that shifted in favour of the Republican party in the 2016 election: Trump won the group of non-college educated whites, for example, by a wider margin than any candidate going back to 1980. Building on these observations, we explore if robots shaped the outcome of the 2016 US presidential election.

Figure 1 presents a non-parametric illustration of our key finding, documenting the positive relationship between differences in the Republican two-party vote share between the 2016 and 2012 elections and changes in the exposure to automation across electoral districts. We show that this relationship remains similar also when controlling for a range of other baseline demographic and economic factors, specialization in manufacturing, and differences in the share of employment that falls in occupations and industries that are more exposed to offshoring, routinization, and trade. The observed relationship also remains when we factor out state-level shifts in voting patterns and exploit differences in exposure across electoral districts located within the same state. To account for the potential endogeneity of robot exposure, we also present additional instrumental variable (IV) estimates that exploit historical differences in industrial specialization across local labour markets and the adoption of robots in countries other than the US to show that this relationship is presumably causal. As a final empirical exercise, we perform a series of back-of-the-envelope calculations to examine how the outcome of the 2016 election would have changed under different counterfactual levels of robot adoption. All else equal, these exercises suggest that in a scenario where the exposure to robots had not increased in the immediate years leading up to the election, the Electoral College would have been won by the Democratic candidate. Although these findings naturally should be interpreted with care, it bolsters the view that that automation in recent years tilted the electorate into opting for radical political change.

The remainder of this paper is structured as follows. We begin by discussing the political economy of automation, showing that economic history has not been a long tale of progress. Despite the technological wonders of the British Industrial Revolution, the first three generations did not experience its benefits. The absence of better paid jobs as the mechanized factory displaced the domestic system led workers to riot against the spread of machinery. In similar fashion, we show that a sizeable share of the American workforce has been left worse off in economic terms as a result of automation. Lastly, we examine the political implications of the robot revolution in terms of its impacts on the outcome of the 2016 US presidential election.

2 The political economy of automation

Why have economic models failed to incorporate the resistance to new technology? One reason is that standard neoclassical theory typically treats automation as a Pareto improvement:

in the event that workers are displaced by machines, new and better-paid jobs become available for everyone. The irrelevance of such models is evident from the historical record: technological change has always been accompanied by what the great economist Joseph Schumpeter famously termed 'creative destruction'. As new technologies displace old ones, they also render the skills of parts of the workforce obsolete. This dilemma is prominently featured in James Joyce's colourful novel *Ulysses* (1922), in which Leopold Bloom takes note of the disruptive force of technology:

> A pointsman's back straightened itself upright suddenly against a tramway standard by Mr Bloom's window. Couldn't they invent something automatic so that the wheel itself much handier? Well but that fellow would lose his job then? Well but then another fellow would get a job making the new invention?[1]

Bloom's observation goes to the heart of creative destruction: as automation makes the jobs of some workers redundant, it also creates new employment opportunities, but for a *different* breed of worker. The surge in child labour that accompanied the spread of the factory system during the early days of the British Industrial Revolution bears witness to this view: the machines of the first factories were made simple enough to be tended by children.[2] As many of the old artisan skills were made obsolete by advances in mechanization, adult male workers lost out: the share of children rapidly expanded and reached about half of the workforce employed in textiles during the 1830s (Tuttle, 1999). As noted by Andrew Ure (1835): 'even in the present day . . . it is found to be nearly impossible to convert persons past the age of puberty, whether drawn from rural or handicraft occupations, into useful factory hands.'[3] In similar fashion, since the beginnings of the age of automation, machines have replaced repetitive assembly workers, machine operatives, secretaries, and paralegals (Autor *et al.*, 2003). Meanwhile, entirely new tasks have emerged, creating demand for a different set of skills, like those of audio-visual specialists, software engineers, database administrators, and computer support specialists (Berger and Frey, 2016, 2017). Consequently, workers without a college education, who have seen their jobs being automated away, have shifted into low-income jobs or non-employment (Cortes *et al.*, 2016a).

This process of creative destruction, upon which long-run growth ultimately rests, has *always* created both winners and losers in the labour market. Because creative destruction comes with social costs—as some workers see their incomes disappear, are forced to migrate, and may experience episodes of unemployment—it may lead to social unrest, in turn threatening the power of incumbent political leaders. Thus, because resistance to new technology

[1]Cited in Akst (2013).

[2]With the aid of machines, spinning was quickly learned and needed little strength: early spinning machines were simple and smaller in size, making them perfectly suitable to be tended by children.

[3]Cited in Mokyr (2009).

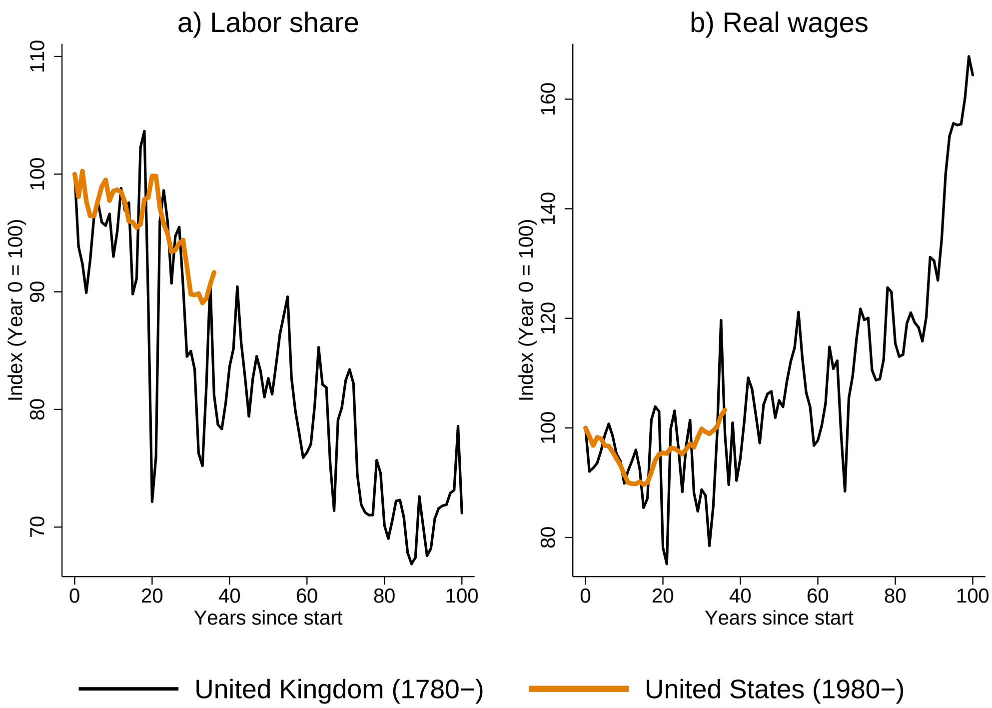
takes place outside the market, the economics and politics of automation are intimately connected. As forcefully argued by Mokyr (1998):

> Any change in technology leads almost inevitably to an improvement in the welfare of some and a deterioration in that of others. To be sure, it is possible to think of changes in production technology that are Pareto superior, but in practice such occurrences are extremely rare. Unless all individuals accept the verdict of the market outcome, the decision whether to adopt an innovation is likely to be resisted by losers through non-market mechanism and political activism.

Ultimately, however, the extent of resistance to automation depends on how its benefits are being shared. During the twentieth century, railroad telegraphers, telephone operators, and longshoremen all lost their jobs to automation. Yet, the continued expansion of manufacturing and rising educational attainment in America allowed most workers to switch into better-paid jobs: the share of national income accruing to the 'middling sort' increased up until the 1970s (Lindert and Williamson, 2016; Gordon, 2016). This period, referred to by economists as the 'great levelling', witnessed rapid advances in automation that made the vast majority of workers better off, prompting President Kennedy to note that 'a rising tide lifts all the boats'. All the same, there is no assurance that workers who see their jobs disappear will find new and better-paid employment opportunities. During times when a greater share of the workforce loses out to automation, it naturally follows that resistance to new technology will be more vehement. Figure 2 documents two such episodes: the British Industrial Revolution and the age of automation in America. During the first six decades of the Industrial Revolution, ordinary Englishmen did not see any of the benefits from mechanization: as output expanded, real wages stagnated, leading to a sharp decline in the share of national income accruing to labour. Notably, the trajectories of the American economy over the four decades following the revolution in automation of the 1980s almost exactly mirror the first four decades of the Industrial Revolution in Britain.

2.1 The rise of the Luddites: evidence from the British Industrial Revolution

The British Industrial Revolution was the defining episode that made technology the chief engine of economic growth and eventually allowed mankind to escape the life that Thomas Hobbes described as 'nasty, brutish, and short'. *Eventually* was nonetheless a long time. Between 1780 and 1840—the *classic* period of the Industrial Revolution—the lives of ordinary workers got nastier, more brutish, and shorter. The standard of living debate surrounding the Industrial Revolution will probably never settle for good, but the optimists have an in-



Notes: This figure shows the labour share of income (*a*) and the trajectories of real wages (*b*) in the United Kingdom starting in 1780 and in the United States starting in 1980. US labour share data is based on the Bureau of Labor Statistics (BLS) labour share index and real wages are calculated from the BLS average weekly earnings of production and non-supervisory employees deflated with a CPI. UK labour share and real wage data is taken from Allen (2009).

Figure 2: A tale of two industrial revolutions

creasingly difficult case to make as empirical evidence continues to accumulate.[4] Almost by any measure, material standards and living conditions for the common Englishman did not improve before 1840. Output expanded, yet the gains from growth did not trickle down to the vast majority of the population. The best estimates suggest that while output per worker increased by 46 per cent over the classic period (Crafts and Harley, 1992), real wages rose by a mere 14 per cent (Feinstein, 1998).[5] Meanwhile, working hours increased by 20 per cent (Voth, 2000), suggesting that hourly wages even declined in real terms.[6] The main beneficiaries were industrialists who saw the profit share of income double (Allen, 2009). The view of Friedrich Engels (1845), that industrialists "grow rich on the misery of the mass of wage earners', was thus largely accurate for the period he observed: as wages declined and the profit share of national income doubled, the income share accruing to the top 5 per cent in Britain almost doubled as well (Lindert, 2000).

Why did living standards during the days of the Industrial Revolution falter? As argued by Allen (2016), the issue of faltering standards of living was the result of the destruction of hand-loom weaving and other manual trades. The displacement of the domestic system by the mechanized factory inflicted substantial pains on the workers that felt the force of the factory. The observation of Baines (1835), that hand-loom weavers were in 'deplorable condition', cannot be explained without reference to the rise of power-loom weaving. Comparing the wages of weavers to occupations left unaffected by technological change, Allen (2016) has shown that poverty accompanies progress as the incomes of hand-loom weavers collapsed in response to the spread of the power loom. Not only did wage inequality grow rapidly; the earnings potential of weavers was reduced to the level of barebones subsistence.

Where did workers who lost their jobs to the force of the factory end up? While we lack individual-level data to trace their fates, recent empirical evidence from Northamptonshire

[4] Economic historians have made many attempts at measuring long-run trends in real wages during this period. The first landmark study was that of Lindert and Williamson (1983), showing that real wages in Britain had already increased after the Battle of Waterloo (1815). Their findings were always controversial, however, especially since they did not concur with findings about patterns of consumption and biological indicators of living standards. In fact, biological indicators suggest that overall material standards, if anything, declined: Floud *et al.* (1990) and Komlos (1998) show somewhat different temporal patterns, but both find that men in 1850 were shorter than they had been in 1760. This finding is consistent with data on *per capita* calorie consumption, which was lower in 1850 relative to 1800 (Allen, 2005). Beyond food consumption, the share of households with a surplus for non-essentials declined among low-wage agricultural labourers and factory workers over the first half of the nineteenth century (Horrell, 1996). New real wage series reflect these trends: based on an updated cost of living index, Feinstein (1998) largely confirmed what we know from patterns of consumption and biological indicators, showing that real wages were stagnant before 1840. Recently, however, Clark (2005) has developed a new price index. Although Clark's (2005) estimates shows that real wages did not improve beyond their mid-eighteenth century level until the 1820s, they are more optimistic than those of Feinstein (1998). All the same, reconciling the differences in the two price indexes, Allen (2009) largely confirms Feinstein's (1998) picture of real wage trends up until 1860.

[5] The real wage index even fell from its base of 100 in 1780 to 84.9 in 1800, just before the outbreak of the Napoleonic Wars, and only increased slightly thereafter.

[6] Voth (2000) documents the increase in working hours for the period 1760 to 1830.

is illustrative (Shaw-Taylor and Jones, 2010). As factory mechanization in Britain left the local worsted cloth industry unable to compete, it flooded the agricultural labour market with former weavers for many decades. The workers that shifted into agricultural jobs were left significantly worse off: the wages of agricultural labourers in Britain were just around twice of barebones subsistence, and significantly lower than those of weavers before their incomes collapsed due to mechanization (Allen, 2016). The flood of ex-weavers could not possibly have been absorbed by the agricultural sector, suggesting that many were left unemployed since the industrial sector did not grow at a sufficient pace to replace the jobs lost in weaving (Shaw-Taylor and Jones, 2010). The benefits of the Industrial Revolution in Northamptonshire were only felt generations after weaving had collapsed, as was also the case in Britain in general.

From an economics point of view, the faltering standards of living during the classic period of the Industrial Revolution represent something of a dilemma: why would workers voluntarily agree to participate in the industrialization process if it reduced their utility? Yet, this is only a puzzle in the absence of coercion. Coercion was, however, far from absent. Clashes between workers and the British government over the adoption of machines were frequent. On 10 May 1768, the first steam-powered sawmill in Limehouse was burned to the ground by sawyers claiming that it had deprived them of employment; in 1772, a factory using Cartwright's power loom in Manchester was similarly burnt down; and the riots of 1779 in Lancashire, where machines had diffused most rapidly, were no less severe than previous episodes.[7] Workers rioted against the increasingly mechanized factory, but efforts to bring the spread of machines to halt were unsuccessful as the British government took an increasingly stern view of any attempts to hinder industrial and technological development, which it deemed critical to Britain's competitive position in trade (Mokyr, 1990; Caprettini and Voth, 2017; Mantoux, 2013; Berg, 1982). During the Luddite risings of 1811–13, rioters achieved nothing more than their predecessors, except forcing the British government to deploy an even larger army: the 12,000 troops sent to resolve the situation exceeded the size of the army which Wellington took into the Peninsula War against Napoleon in 1808. As argued by Mantoux (2013): 'Whether their resistance was instinctive or considered, peaceful or violent, it obviously had no chance of success, as the whole trend of events was against it.'

2.2 The age of automation and its victims

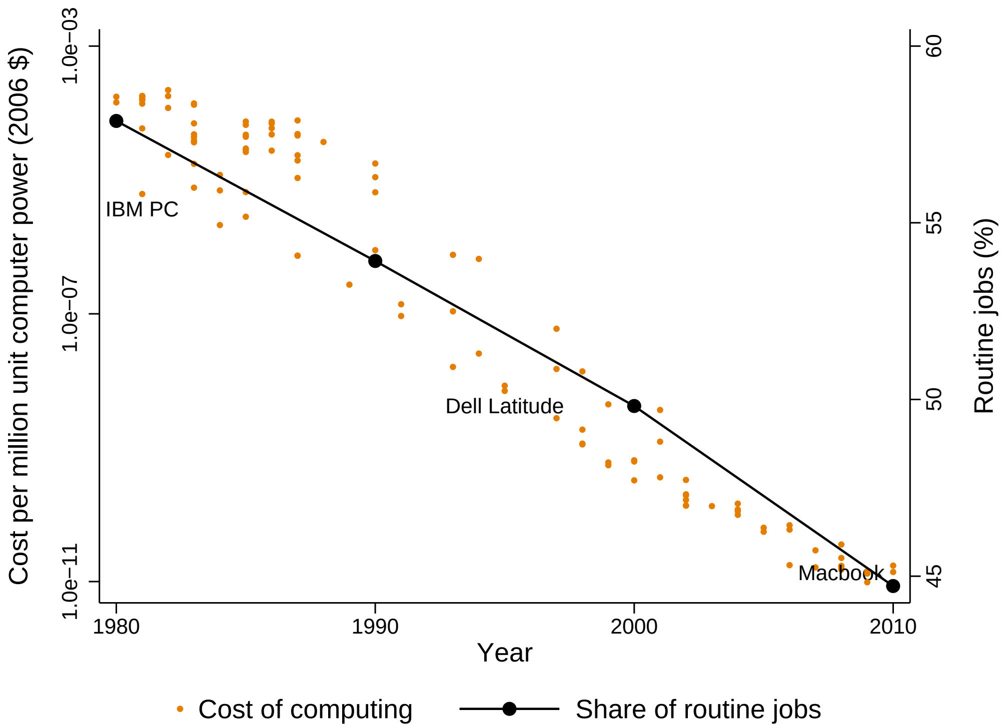
Like in the early days of the Industrial Revolution, growth has failed to trickle down to ordinary Americans since the age of automation began in the early 1980s. Over the period 1979

[7]Moreover, using newly-compiled data on the diffusion of threshing machines, Caprettini and Voth (2017) show that labour-saving technology was the key determinant of the probability of unrest during the 'Captain Swing' riots of the 1830s. Where machines were adopted, the probability of riots was around 50 per cent higher: machines themselves were the key cause of their concerns.

to 2013, productivity growth was eight times faster than hourly compensation: as productivity grew by 64.9 per cent, hourly compensation for 80 per cent of the American workforce grew only by 8.2 per cent, while the top 1 per cent of earners saw cumulative gains in annual wages of 153.6 per cent (Bivens *et al.*, 2014). The real wages of the vast majority of Americans thus stagnated or even declined. With the exception of a brief period in the late 1990s, the wages of middle-income workers were either flat or in decline, while the wages of low-wage workers fell by 5 per cent. The greatest reversal of fortunes has taken place since the turn of the twenty-first century: between 2000 and 2013, hourly wages fell for the bottom 30 per cent and were flat for the next 40 per cent (Bivens *et al.*, 2014). As was the case during the classic years of the Industrial Revolution, most growth has accrued to owners of capital; the labour share of income in America fluctuated around 64 per cent during the post-war period, but has trended downward since the 1980s, reaching its lowest post-war level after the Great Recession, and is now averaging 6 percentage points below the level that prevailed during the first four decades of the post-war period (see Figure 2). Thus, a large segment of the workforce has become detached from the engine of growth. According to estimates by Summers (2015), the income distribution of 1979 would leave today's top 1 per cent with $1 trillion less in annual income, while adding on average $11,000 a year for a family in the bottom 80 per cent.

Although the causes of this detachment are still being debated, a growing body of work has identified automation as one of the prime forces driving the shifts in income shares along the occupational wage distribution (Autor *et al.*, 2003, 2006; Autor and Dorn, 2013; Graetz and Michaels, 2015; Michaels *et al.*, 2014; David, 2015), and from labour and owners of capital (Karabarbounis and Neiman, 2013), downplaying alternative—albeit complementary—explanations emphasizing the role of globalization, immigration, deunionization, and manufacturing decline. Across geographies and industries, the trillion-fold secular decline in the price of computing (Nordhaus, 2007), has caused a sharp reduction in the demand for routine jobs—like those of machine operators, assembly workers, and bookkeepers—that can be performed by robots and computers (see Figure 3). In recent years, this process has speeded up: while the disappearance of *per capita* employment in routine occupations has been a key feature of the US labour market since the 1980s, it has not been a gradual phenomenon. Most routine employment loss has happened during economic downturns and has more recently been accelerated by the Great Recession. Though employment in high- and low-skill occupations has rebounded since 2009, the recovery for middle-income routine employment has been jobless. Jobless recoveries were not observed in routine occupations prior to the age of automation, suggesting that joblessness has been driven by technology (Jaimovich and Siu, 2012).

Where have workers who lost their jobs to automation reallocated? An emerging literature suggests that advances in automation has caused many workers to transition into either non-



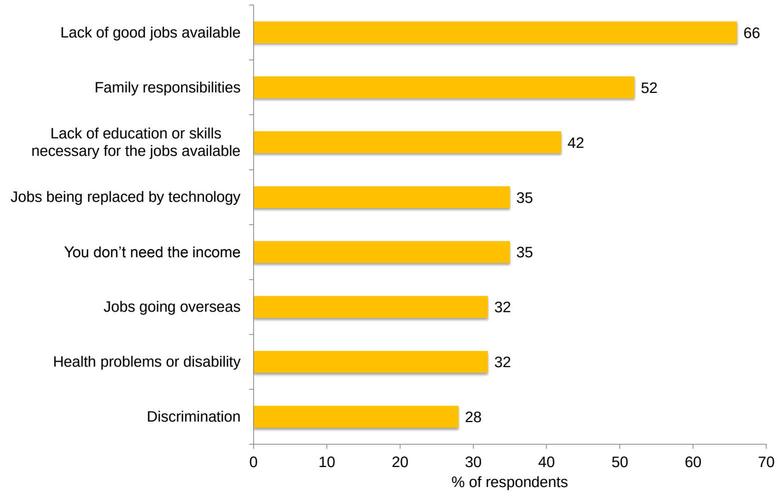
Notes: This figure shows the rapid decline in computing costs for a variety of models launched betwen 1980 and 2010 based on (updated) data from Nordhaus (2007) and the declining share of US employment in routine jobs over the same period based on calculations from public use census data for 1980–2010 obtained through the Integrated Public Use Microdata Series (IPUMS) (Ruggles *et al.*, 2010) and the definition of routine jobs in Jaimovich and Siu (2012).

Figure 3: Computers and the decline of routine jobs in the United States, 1980–2010

employment or non-routine manual jobs (Cortes *et al.*, 2016a). In tandem with routine jobs disappearing, Autor and Dorn (2013) document a structural shift in the labour market, with workers reallocating their labour supply to low-income service occupations. Arguably, this is because the manual tasks of service occupations are less susceptible to robots, as they require a higher degree of flexibility and physical adaptability (Acemoglu and Autor, 2011; Autor *et al.*, 2003; Goos and Manning, 2007; Goos *et al.*, 2009, 2014). Deteriorating median wages are directly linked to such shifts: routine occupations tend to occupy the middle of the wage distribution, whereas manual non-routine occupations (e.g. janitors and building cleaners, personal and home care aides) cluster at the bottom (Autor and Dorn, 2013; Goos and Manning, 2007).

The decline in routine employment is particularly evident among low-skilled prime-aged men in routine physical occupations and prime-aged women with intermediate levels of education in routine cognitive occupations. As shown by Cortes *et al.* (2016a), these same groups account for a substantial fraction of both the increase in non-employment and employment in low-wage, non-routine manual occupations observed during the same time period. More direct evidence of advances in automation leading to non-employment has recently been provided by Acemoglu and Restrepo (2017), documenting a robust negative impact of robots on employment and wages. Yet, while robots affected both men's and women's jobs, the effect on male employment was up to twice as big. Their findings speak to the labour market trends observed by Eberstadt (2016), showing that 24 per cent of men between 25 and 54 will be out of work by 2050 at current trend.

Moreover, the decoupling of average and median real wages can in part be explained by the falling cost of automation, contributing the substantial employment growth in occupations involving cognitive tasks where skilled labour has a comparative advantage, as well as the persistent increase in returns to education (Katz and Murphy, 1992; Acemoglu, 2002; Autor and Dorn, 2013). While college-educated men have fared much better relative to their low-skilled counterparts by shifting into high-income cognitive occupations, improvements in labour market outcomes were not experienced equally by both genders. Despite the rapid growth in employment in high-income cognitive occupations, the probability that a college-educated male was employed in one of these jobs has fallen since the age of automation (Cortes *et al.*, 2016b). The relative prominence of college-educated women in such jobs can be explained by an increase in the demand for social skills in such occupations, where the psychology and neuroscience literatures indicate that women have a comparative advantage. Thus, in short, the prime victims of the robot revolution have been low-skilled men; the winners have been college-educated women.



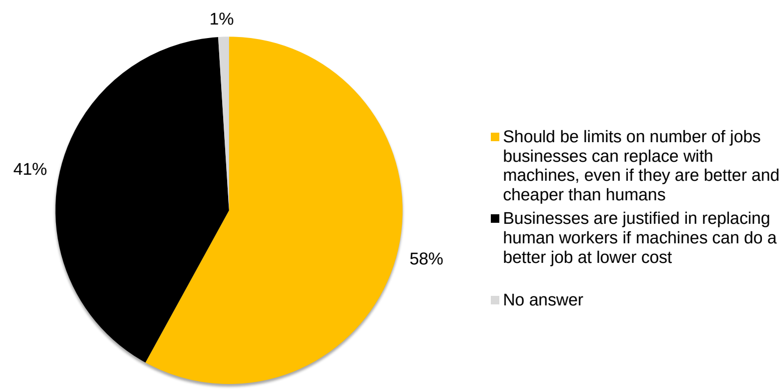
Notes: This figure reports the percentage of respondents (who are unemployed but able to work) who state that each factor is a major or minor reason why they are not working in a 2014 Kaiser Family Foundation/New York Times/CBS News survey based on interviews with 1,002 respondents between the ages of 25 and 54 who are currently not employed either full-time or part-time. See Hamel *et al.* (2014) for more information.

Figure 4: Why are Americans not working?

3 Robots and the 2016 US presidential election

We next turn to examine if the increased adoption of robots caused American voters to opt for radical political change. Of course, Trump did not make any pledge to bring technological progress to a halt during his election campaign. In fact, he barely mentioned technology at all. Yet, his pledge to bring back jobs in mining and manufacturing, which have long been automated away, bears with it an implicit promise to restrict automation, although few voters will have noted this logic. All the same, it remains indisputable that Trump represented a challenge to the political *status quo*; fully 82 per cent of voters believed that Trump was the candidate for change, according to the exit polls.

Although many voters are unlikely to have recognized the true causes of their concerns, automation was identified as one of the key reasons behind their economic misfortunes prior to the election. A 2014 survey by the Kaiser Family Foundation/New York Times/CBS News of prime working-age adults (i.e. aged between 25 and 54) that were unemployed yet able to work, for example, suggests that technology indeed was one of the perceived culprits of their detachment from the labour market: more than a third of respondents (35 per cent) stated that jobs being replaced by technology was a reason they were not working, which is a larger share than that citing discrimination, health problems, or jobs going overseas to account for their joblessness (see Figure 4). Moreover, among the most commonly reported reasons for

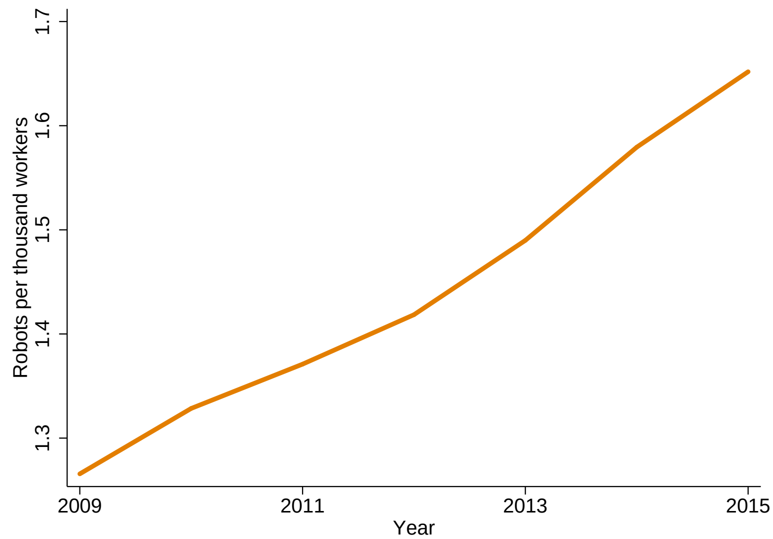


Notes: This figure shows the percentage of Americans who state that there should (not) exist limits on the number of jobs that businesses can replace with machines based on a 2017 Pew Research Center survey of 4,135 US adults. See Pew Research Center (2017) for more information.

Figure 5: A return of the Luddites?

non-employment were a lack of 'good jobs' and sufficient education and skills for the jobs available, which in light of the discussion in the previous section arguably are both deeply intertwined with technological changes. At the same time, more than half (58 per cent) of Americans in a more recent Pew Research Center survey stated that there should be limits to the number of jobs firms can displace with machines, even if they can do the job better at lower cost (see Figure 5). Although such survey evidence does not shed light on voting patterns in the 2016 election, they suggest the widespread concern about automation and support for policies aimed at restricting it.

Identifying the workers that have lost out to automation is empirically challenging, yet it is evident from a series of studies that automation has led to the displacement of workers particularly in routine or middle-skill occupations which has led to a polarization of the US labour market (Autor *et al.*, 2003; Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos and Manning, 2007; Goos *et al.*, 2009, 2014; Jaimovich and Siu, 2012), and that this oncoming rush of automation has affected locations in very different ways. In particular, a recent study by Acemoglu and Restrepo (2017) has shown that workers in labour markets that were more exposed to the adoption of robots in the 1990s and early 2000s experienced reductions in both employment and wages, suggesting that workers in those locations have lost out to automation. We follow a similar approach, exploiting temporal differences in the penetration



Notes: This figure shows the number of industrial robots per thousand workers in the United States based on data from the IFR and the BLS. Note that the IFR only reports aggregated data for North America and that the US robot count therefore includes robots located in Canada and Mexico prior to 2010, though the vast majority of the North American operational stock is located in the United States in these years.

Figure 6: Industrial robots in the United States, 2009–15

of robots across industries and differences in industrial specialization across electoral districts to identify whether areas that were more exposed to automation in the years running up to the 2016 election were also more likely to swing in favour of Trump.

3.1 Measuring the exposure to automation

To measure robot exposure across local labour markets, we collect data from the International Federation of Robotics (IFR) that compiles annual counts of robots used by country and industry from the early 1990s through 2015. Industrial robots are defined by the IFR as 'automatically controlled, reprogrammable, and multipurpose' machines that are autonomous (i.e. not in need of human operators) and that can flexibly be adapted to perform a variety of tasks. Thus, while textile looms are not industrial robots according to the definition applied by the IFR, the vast majority of machines handling a variety of tasks such as assembly, packaging, or welding are represented in our data. While this leaves out many potentially important technologies (e.g. algorithms or other forms of software) it provides a useful source of consistently defined information on investments in automation technology across US industries as demonstrated by Acemoglu and Restrepo (2017).

As shown in Figure 6, there has been a secular increase in the use of robots in the United States over the period, which resulted in an operational stock of about 1.7 robots per thousand workers in 2015. In our analysis, we focus on changes in robot use between the immediate years prior to the last two elections (2011–15) for which we can match information on the robot stock in 13 manufacturing industries and six broad non-manufacturing sectors, as in Acemoglu and Restrepo (2017), to information on the employment structure of local labour markets, which in our analysis correspond to the 722 commuting zones (CZs) that exhaust the mainland United States.[8] To identify the industrial composition of each CZ, we rely on data from the 2011 American Community Survey (ACS) that provides a 1-per cent sample of the US population (Ruggles *et al.*, 2010), to which we can match the industry-level IFR data on robot use.

We estimate changes in the exposure to robots (EI_j) between 2011 and 2015 for each CZ j as:

$$EI_j = \sum_{i \in I} l_{ij,2011} \times \left(\frac{R^{US}_{i,2015}}{L^{US}_{i,2011}} - \frac{R^{US}_{i,2011}}{L^{US}_{i,2011}}\right) \tag{1}$$

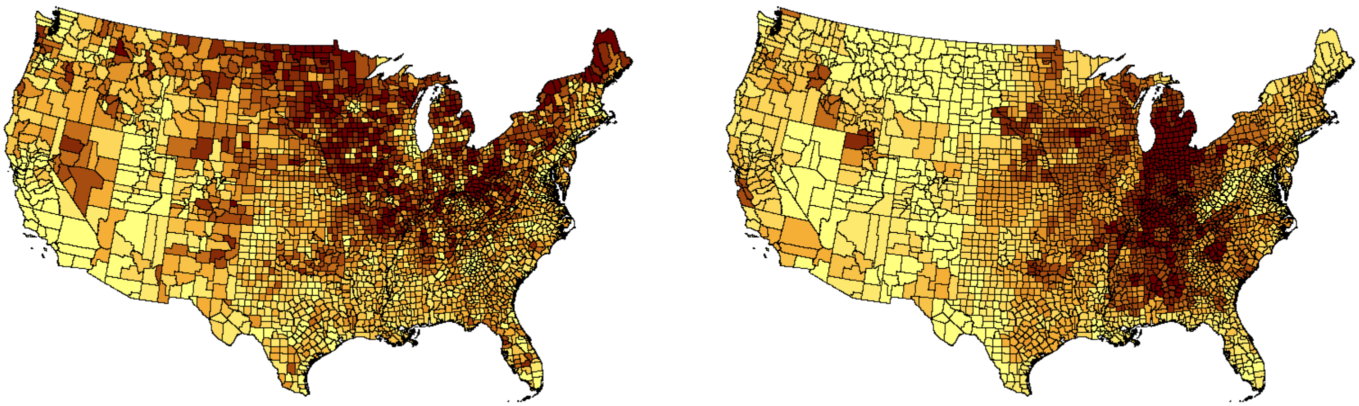
where $l_{ij,2011}$ corresponds to the share of CZ's j employment in industry i in 2011 computed from the ACS data, and $\frac{R^{US}_{i,t}}{L^{US}_{i,t}}$ denotes the national level of robot usage per thousand workers in industry i in year t. Intuitively, this measure thus reflects differences in exposure to robots across CZs driven by variation in the penetration of robots across US industries between 2011 and 2015 and initial differences in industry specialization across CZs, with a higher level of exposure in areas that are more heavily specialized in industries that experienced a greater penetration of robots.

To examine the link between differences in the exposure to robots and the propensity of voters to opt for Trump, we crosswalk county-level data on the distribution of votes from the 2016 and 2012 elections from Dave Leip's *Atlas of US Presidential Elections* to their corresponding CZ. Throughout the analysis, we focus on differences in the Republican two-party vote share between the 2016 and the 2012 elections that align with changes in the exposure to robots between the immediate years prior to each election.

3.2 OLS estimates

As shown in Figure 1 in the introduction, the Republican two-party vote share increased more between the 2012 and 2016 elections in electoral districts that saw an increased exposure to robots over the same period. A link between increased automation exposure and a higher share of voters opting for Trump is further underlined by the geographical overlap evident in

[8]Outside of manufacturing, we construct the data for the use of robots in six broad industries: agriculture, forestry, and fishing; mining; utilities; construction; education, research, and development; and other non-manufacturing industries (e.g. services and entertainment). In manufacturing, there are consistent data on the use of robots for a set of 13 industries: food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles; and other manufacturing industries. These industries roughly correspond to the three-digit level.



(a) Changes in the Republican two-party vote share (b) Changes in the exposure to robots

Notes: These figures show differences in the Republican two-party vote share between the 2016 and 2012 elections and changes in the exposure to robots across counties (CZs) between the immediate years prior to the last two elections, where each variable is divided into deciles with darker shades corresponding to an increase in the votes cast for the Republican candidate and exposure to robots respectively. County boundaries are based on maps obtained from IPUMS NHGIS (www.nhgis.org).

Figure 7: Exposure to robots and the vote for Trump in the 2016 presidential election

Figure 7 that maps changes in the exposure to robots across counties (CZs) and changes in the Republican two-party vote share, with a substantially higher exposure to robots in many areas that also saw increasing support for the Republican candidate in 2016. Yet, while these patterns are highly suggestive, they may at the same time reflect a wide variety of potentially confounding factors. We therefore next proceed to analyse this relationship when controlling for other potential determinants of voting outcomes by estimating OLS regressions on the following form:

$$\triangle V_{cjs} = \alpha + \delta EI_j + \gamma_s + \mathbf{X_j}\theta + e_{cjs,} \tag{2}$$

where the outcome variable $\triangle V_{cjs}$ is the percentage point difference in the Republican two-party vote share between the 2016 and the 2012 elections in county c, in CZ j, located in state s. The variable of interest is EI_j, which corresponds to the CZ-level exposure to robots as defined in the previous section. $\mathbf{X_j}$ is a vector of CZ-level control variables including a variety of baseline (2011) demographic and labour market characteristics that are mainly calculated based on the ACS data. Additional estimations also include state fixed effects (γ_s) to examine whether the potential link between support for Trump and the exposure to robots exists when factoring out state-level differences in exposure and shifts in voting patterns. All regressions are weighted by the total number of votes in the 2016 election and standard errors are clustered at the CZ-level throughout.

Table 1 presents OLS estimates of equation (2) documenting the positive and highly statistically significant association between changes in robot exposure and changes in the share

	Outcome: change in Republican two-party vote share, 2016 (Trump) vs 2012 (Romney)					
	(1)	(2)	(3)	(4)	(5)	(6)
Changes in the exposure to robots	2.015***	1.481***	0.978***	1.157***	1.244***	0.545**
	(0.501)	(0.166)	(0.141)	(0.220)	(0.209)	(0.240)
Standardized coef.	0.294	0.216	0.143	0.169	0.181	0.079
Labour market controls?	No	Yes	Yes	Yes	Yes	Yes
Demographic controls?	No	No	Yes	Yes	Yes	Yes
Broad industry controls?	No	No	No	Yes	Yes	Yes
Offshoring, routine jobs, and trade?	No	No	No	No	Yes	Yes
State fixed effects?	No	No	No	No	No	Yes
Observations	3,108	3,108	3,108	3,108	3,108	3,108
R-squared	0.086	0.350	0.508	0.516	0.527	0.646

Notes: This table presents OLS estimates of equation (2) in the main text. The outcome is the percentage point difference in the Republican two-party vote share between the 2016 and 2012 elections (across the counties in our sample the mean difference is 5.88 percentage points with a s.d. of 5.22), while the main right-hand side variable is the change in robot exposure (mean 0.82 with a s.d. of 0.80). Column 2 controls for population, unemployment rates, and whether a CZ is part of a metropolitan area. Column 3 adds controls for age groups and the share of the population that is Asian, black, college educated, female, foreign born, and Hispanic, respectively. Column 4 adds the share employed in manufacturing, the female share of manufacturing employment, and the share in durable manufacturing and construction, respectively. Column 5 includes additional controls for exposure to Chinese imports betweeen 1991 and 2011 and the start of the period share of employment in offshorable and routine jobs, respectively. All regressions are weighted by each county's total number of votes in the 2016 election. Statistical significance based on standard errors clustered at the CZ-level (reported in parentheses) is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 1: Changes in the exposure to robots and the Republican two-party vote share: OLS estimates

of votes cast in favour of the Republican candidate. As reflected in the standardized coefficients, a one-standard-deviation increase in the exposure to robots is associated with an 0.294 standard-deviation-increase in the Republican two-party vote share (column 1). Put differently, the point estimate of 2.015 implies that if we compare two counties at the 25th and 75th percentile of robot exposure respectively, the Republican two-party vote share in the county with a higher level of exposure is predicted to increase by an additional 1.330 percentage points in 2016.[9] Of course, this bivariate relationship could simply reflect that differences in the exposure to robots is correlated with a variety of omitted factors: areas with a higher exposure to robots also have, for example, lower educational levels, higher initial unemployment rates, and are more likely to be rural than areas with a lower exposure.

To account for such factors, column 2 adds a set of basic labour market controls. Specifically, we control for start-of-the-period differences in population and unemployment rates, as well as whether a CZ is part of a metropolitan area. Because voting patterns are reported to have varied substantially along a variety of demographic dimensions that also may be correlated with differences in the exposure to robots, column 3 further adds controls for initial differences in age composition of the labour force and the share of the population that is Asian, black, college educated, female, foreign born, and Hispanic, respectively.[10] Although the estimated link between robot exposure and an increased vote share for the Republican candidate declines in magnitude when adding these demographic and labour market controls, it remains sizeable and highly statistically significant.

As the vast majority of robots are used in manufacturing industries, it raises the concern that our estimated impacts of robot exposure partly reflect a specialization in industrial work. In column 4, we further add the start-of-the-period share employed in manufacturing, the female share of manufacturing employment, and the share in durable manufacturing and construction, respectively. Along similar lines, the increased exposure to robots may be correlated with differences across CZs in the exposure to offshoring, routinization, or trade competition. Column 5 therefore also adds controls for the start-of-the-period share of the population employed in offshorable and routine jobs following a similar approach in classifying occupations as offshorable and routine as Autor and Dorn (2013), as well as the exposure of the workforce to Chinese imports between 1991 and 2011 based on data from Autor *et al.* (2013).[11] Notably, the estimates remain similar in magnitude and statistical precision when adding these additional controls, which presumably reflects the considerable variation

[9] Across the counties in our sample, the 25th and 75th percentile of robot exposure is 0.33 and 0.99 respectively that implies an estimated increase in the Republican two-party vote share of $2.015 \times (0.99 - 0.33) = 1.330$ percentage points.

[10] For brevity we do not report the estimates for these additional covariates, but note that they generally align with popular perceptions of the areas that supported Trump: the support was significantly lower, for example, in areas with a more educated population, or where blacks or Hispanics constituted a large share of the population.

[11] Autor *et al.* (2016b) and Autor *et al.* (2016a) further document the impacts of import competition on political polarization in the United States as well as the 2016 presidential election.

in robot use *within* manufacturing and the relatively limited overlap between robot exposure and exposure to Chinese imports, offshoring, and specialization in routine work (Acemoglu and Restrepo, 2017). Although the estimated magnitude declines in column 6 when we also add a full set of state fixed effects, thus only exploiting within-state variation, a positive and highly statistically significant link between changes in the exposure to robots and changes in the Republican two-party vote share persists. Overall, these estimates thus lend strong support to the notion that the correlation observed in Figure 1, showing that areas that saw an increasing exposure to robots also were more likely to swing in favour of Trump in the 2016 election, does not simply reflect observable differences in, for example, demographics between more and less exposed areas.[12]

3.3 IV estimates

A central identification challenge is that the exposure to robots may be correlated with a variety of local economic shocks that may in turn have shaped the outcome of the election. While our rich set of controls alleviates some concerns along these lines, it is still possible that areas that saw a rising exposure to robots and shifted in favour of Trump at the same time may have experienced unobserved shocks that we fail to control for. We address such concerns by developing two alternative IV strategies. First, we isolate exogenous variation in the exposure to robot adoption by exploiting historical differences in industrial specialization that is less likely to correlate with other adverse shocks potentially correlated with differences in the exposure to robots. To construct our first instrument, we replace the 2011 distribution of CZ employment with employment shares in 1980 based on census data (Ruggles *et al.*, 2010), which enables us to focus on historical and persistent differences in the specialization of CZs in different industries thus also avoiding any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes (Acemoglu and Restrepo, 2017). Using the same notation as above, we thus construct the instrument for each individual CZ j as:

$$EI_j^{IV1} = \sum_{i \in I} l_{ij,1980} \times \left(\frac{R_{i,2015}^{US}}{L_{i,2011}^{US}} - \frac{R_{i,2011}^{US}}{L_{i,2011}^{US}}\right) \tag{3}$$

A second way to isolate exogenous variation in the exposure to robots across industries is to exploit cross-industry differences in adoption in countries *other* than the US, which approximates the adoption of robots on the technological frontier. Our second instrument

[12] An additional concern evident from the distribution of robot exposure depicted in Figure 1 is that our results may be sensitive to outliers with the highest level of exposure that also saw the largest increases in the Republican two-party vote share. Reassuringly, however, excluding the top 1, 2, or 5 per cent of counties in terms of their exposure leaves the estimates virtually unchanged both in magnitude and statistical precision (not reported).

therefore focuses on variation in robot usage across industries in ten European countries: Austria, Czech Republic, Denmark, Finland, France, Germany, Italy, Spain, Sweden, and the United Kingdom. We aggregate the IFR robot data to be compatible with the EU KLEMS industrial employment data (Jäger, 2016), which yields 16 industries based on ISIC Rev 4 that requires us to also map the US employment composition to this industrial structure.[13] We then construct the second instrument for each CZ j as follows:

$$EI_j^{IV2} = \sum_{i \in I} l_{ij,1980} \times (mean(\frac{R_{i,2015}}{L_{i,2011}}) - mean(\frac{R_{i,2011}}{L_{i,2011}})) \tag{4}$$

where $mean(\frac{R_{i,t}}{L_{i,t}})$ denotes the average robot usage among European countries in industry i and year t, and $l_{ij,1980}$ corresponds to the 1980 share of a CZ's j employment in industry i. The variation in the instrument is thus derived from historical differences in industrial specialization across CZs and changes in average robot use in industries in countries outside of the United States.

As a large literature has emphasized that weak instruments may lead to severe bias, it is reassuring that a strong first-stage relationship exists between our first instrument and changes in the exposure to robots, which presumably reflects the persistence in industrial specialization across local labour markets. Indeed, the Kleibergen–Paap F-statistics reported at the bottom of Table 2 suggest that our first instrument remains a strong predictor of robot exposure when also conditioning on the rich set of additional controls and state fixed effects. Although the second instrument also performs well in the simpler first stage, it is considerably weaker in the more demanding specifications, which likely reflects that fewer industries are available in the EU KLEMS data, thus resulting in a lower resolution in the mapping of robot use to CZ employment shares.

Table 2, panels A and B, report the second-stage 2SLS estimates using the two instruments respectively showing that there exists a strong relationship between changes in the exposure to robots and the Republican two-party vote share. Indeed, our 2SLS estimates are all positive and typically highly statistically significant, suggesting that the finding that areas that saw an increased exposure to robots also saw increases in the share of votes cast in favour Trump reflects a causal relationship. Panel A, column 1 presents the most parsimonious specification, using the instrument that derives its exogenous variation from historical (1980) differences in industrial specialization across CZs, while columns 2–6 sequentially add the same set of controls discussed in the previous section, as well as state fixed effects,

[13] These industrial sectors are respectively: agriculture/forestry/fishing, mining/quarrying, foods/beverages/tobacco (10–12), textiles/wearing apparel/leather (13–15), wood/paper/printing (16–18), chemicals/chemical products (19–21), rubber/plastics/non-metallic mineral products (22–23), basic metals and metal products (24–25), electrical and optical equipment (26–27), machinery (28), transport equipment (29–30), other manufacturing (31–33), electricity/gas/water supply, construction, education, all other non-manufacturing.

respectively. As shown in these estimates, the positive relationship between changes in the exposure to robots and changes in the Republican two-party vote share persists and suggests that a one-standard-deviation increase in robot exposure leads to an 0.191-standard-deviation increase in the share of votes cast for Trump (column 6). Panel B presents 2SLS estimates from similar specifications, instead using the alternative instrument in the first stage, which derives its exogenous variation in robot exposure from historical differences in industrial specialization across CZs and the average rate of robot adoption across industries in European countries. Although these results should be interpreted somewhat more carefully, given that the instrument is a less strong predictor of differences in exposure in the more extensive specifications, it is reassuring that the second-stage estimates consistently return a positive and generally statistically significant link between changes in robot exposure and changes in the Republican two-party vote share that are broadly in line with the estimates reported in panel A.

Together, these results show that the correlations documented in the previous section are plausibly causal and that the simple correlation between robot exposure and the support for Trump, if anything, is likely to understate the effects of robots on the 2016 presidential election. Yet, while the finding that electoral districts that became more exposed to automation during the years running up to the election were more likely to vote for Trump is an interesting and important result in itself, it does not shed light on the extent to which this impact shaped the outcome of the election.

3.4 Did robots swing the 2016 US presidential election?

While the above-reported results document a direct positive link between changes in the exposure to robots and the support for the Republican candidate in the 2016 election, they do not shed light on whether the outcome of the election would have changed in a counterfactual scenario with a lower penetration of robots. We next provide such a counterfactual exercise, showing that if the exposure to robots had not increased in the years running up to the vote, the election would have swung in favour of the Democratic candidate.

To examine how the outcome of the 2016 election would have changed if the pace of robot adoption had slowed down, we perform a variety of counterfactual estimates based on our most conservative and preferred IV estimate in column 6 of Table 2, panel A, which indicates that Trump gained on average 1.309 percentage points of the two-party vote share for each unit increase in the exposure to robots in a county. Using this estimate, we first compute the share of the two-party vote that the Republican candidate would have lost if the exposure to robots had been Y per cent smaller, as $1.309 \times (Y\% \times EI_j)$ for each county in our sample. Then, we multiply this share with the number of two-party votes in each county to obtain the number of votes that Trump would have lost to Clinton in the counterfactual

	Outcome: change in Republican two-party vote share, 2016 (Trump) vs 2012 (Romney)					
	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. IV: historical (1980) CZ employment shares and US robot adoption					
Changes in the exposure to robots	1.717***	2.068***	1.339***	1.801***	1.884***	1.309***
	(0.551)	(0.398)	(0.199)	(0.336)	(0.344)	(0.381)
Standardized coef.	0.250	0.302	0.195	0.263	0.275	0.191
	Panel B. IV: historical (1980) CZ employment shares and European robot adoption					
Changes in the exposure to robots	2.604***	2.758***	1.584***	3.622**	4.500**	6.758
	(0.883)	(0.696)	(0.361)	(1.481)	(2.073)	(5.927)
Standardized coef.	0.380	0.402	0.231	0.528	0.656	0.986
Labour market controls?	No	Yes	Yes	Yes	Yes	Yes
Demographic controls?	No	No	Yes	Yes	Yes	Yes
Broad industry controls?	No	No	No	Yes	Yes	Yes
Offshoring, routine jobs, and trade?	No	No	No	No	Yes	Yes
State fixed effects?	No	No	No	No	No	Yes
Kleibergen–Paap F-stat (panel A/B)	714.7/20.6	695.6/21.5	543.2/18.5	112.9/4.7	106.3/3.6	38.0/1.0
Observations	3,108	3,108	3,108	3,108	3,108	3,108

Notes: This table presents 2SLS estimates of equation (2) in the main text. The outcome is the percentage point difference in the Republican two-party vote share between the 2016 and 2012 elections (across the counties in our sample the mean difference is 5.88 percentage points with a s.d. of 5.22), while the main right-hand side variable is the change in robot exposure (mean 0.82 with a s.d. of 0.80). In panel A, we use the variation in robot exposure based on the CZ distribution of employment in 1980 and robot adoption across US industries as an instrument. In panel B, we use the 1980 distribution of CZ employment and the average adoption of robots across industries in European countries as an instrument. See the notes to Table 1 for a description of the additional controls. All regressions are weighted by each county's total number of votes in the 2016 election. Statistical significance based on standard errors clustered at the CZ-level (reported in parentheses) is denoted by: *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Table 2: Changes in the exposure to robots and the Republican two-party vote share: 2SLS estimates

scenario of lower robot exposure. Lastly, we aggregate the counterfactual county vote totals within each state and allocate the implied electoral votes to identify the victor.

Table 3 reports results from this exercise, showing the winner and the vote margin in favour of Trump in a set of closely contested states and aggregate changes in the electoral votes going to Trump and Clinton, respectively, under different counterfactual scenarios of robot exposure had it been 10, 75, or 95 per cent lower. Already at a 10 per cent lower robot exposure, our estimates predict that Michigan would have swung in favour of the Democratic candidate, whereas in a scenario where the use of robots virtually did not increase in the years leading up to the election (i.e. with a 95 per cent lower exposure) Trump would additionally have lost both Pennsylvania and Wisconsin, thus leaving Clinton with a majority in the Electoral College. While this counterfactual exercise naturally should be interpreted carefully, it does suggest that automation had potentially pervasive effects on the outcomes of the 2016 election as it had severe impacts in several contested states.

4 Concluding remarks

The politics of automation has shaped our economic trajectories for millennia. Prior to the 'great escape' brought by the Industrial Revolution, political leaders frequently banned any labour-saving technology for fear of social unrest, providing one explanation for why economic growth was stagnant for most of human history (Acemoglu and Robinson, 2013; Mokyr, 1990). The British government was the first to consistently and vigorously take action against any attempts to hinder the spread of machines, offering 'another explanation why Britain's Industrial Revolution was first' (Mokyr, 1992). The long-term benefits of the Industrial Revolution have been immense and indisputable: prior to 1750, *per capita* incomes in the world doubled every 6,000 years; thereafter, it has taken some 50 years for incomes to double (DeLong, 1998). Even the poorest British citizens today enjoy goods and services in an abundance that was unimaginable to their pre-industrial ancestors. But those benefits came at the expense of three generations of Englishmen (see Figure 2), of whom many were made worse off by the force of technology (Shaw-Taylor and Jones, 2010; Allen, 2016; Baines, 1835; Allen, 2009).[14] To borrow David Landes (2003) phrase:

> if mechanization opened new vistas of comfort and prosperity for all men, it also destroyed the livelihood of some and left others to vegetate in the backwaters of the stream of progress. [...] the victims of the Industrial Revolution numbered in the hundreds of thousands or even millions.

[14] Thus, economic historians have long debated if the Industrial Revolution was 'worth it' (see Williamson, 1982).

	Actual outcome of 2016 election			Counterfactual outcomes due to a lower exposure to robots					
				10% lower		75% lower		95% lower	
	Winner	Margin (# votes)	Margin (% of votes)	Winner	Margin (%)	Winner	Margin (%)	Winner	Margin (%)
Georgia	Republican	211,141	5.10	Republican	5.03	Republican	4.57	Republican	4.42
Arizona	Republican	91,234	3.50	Republican	3.46	Republican	3.18	Republican	3.10
North Carolina	Republican	173,315	3.66	Republican	3.57	Republican	3.01	Republican	2.83
Florida	Republican	112,911	1.19	Republican	1.16	Republican	0.96	Republican	0.90
Pennsylvania	Republican	44,292	0.72	Republican	0.64	Republican	0.15	Democrat	-0.01
Wisconsin	Republican	22,748	0.76	Republican	0.66	Democrat	–0.05	Democrat	-0.26
Michigan	Republican	10,704	0.22	Democrat	-0.20	Democrat	–2.92	Democrat	-3.75
New Hampshire	Democrat	–2,736	–0.37	Democrat	-0.44	Democrat	–0.92	Democrat	-1.06
Minnesota	Democrat	–44,593	–1.51	Democrat	-1.60	Democrat	–2.13	Democrat	-2.30
Electoral votes Trump		306		290		280		260	
Electoral votes Clinton		232		248		258		278	

Notes: This table presents the winner and the vote margin in favour of the Republican candidate in the 2016 election in a set of closely contested states and in terms of total electoral votes, as well as counterfactual outcomes where we estimate how state-level voting outcomes would have changed in a scenario with lower levels of robot exposure based on our estimate in column 6 of Table 2, panel A. See the main text for a further discussion of these estimates.

Table 3: Counterfactual outcomes in closely contested states and the 2016 election

Could the British Industrial Revolution have happened if ordinary workers were also voters? Of course, there is no way of running the experiment, but many did their utmost to bring the spread of machines to a halt by the means they had: besides the flood of petitions against machines that came into parliament, workers voted against machines with sticks and stones (Mantoux, 2013).[15] As an analogy, Wassily Leontief famously suggested that, "If horses could have joined the Democratic party and voted, what happened on farms might have been different."[16] Instead, the proliferation of automobiles, tractors, and trucks caused the annihilation of the horse as a prime mover on farms and as a mean of moving goods and people around. While the robot revolution has not rendered the workforce redundant, many Americans have lost the race to technology, which is reflected in the reallocation of millions of workers from middle-income jobs to low-income occupations or non-employment as their jobs have been automated away (Autor and Dorn, 2013; Cortes *et al.*, 2016a; Acemoglu and Restrepo, 2017). This paper has shown that the victims of the robot revolution have a higher propensity to opt for radical political change by providing evidence that electoral districts with higher exposure to robots were significantly more likely to support Trump.

Looking forward, automation is likely to become a growing political challenge.[17] The potential scope of automation now extends well beyond industrial robots. Recent developments in artificial intelligence and mobile robotics are widely regarded the beginnings of a 'Second Machine Age'; machines are now able to perform even a wider range of non-routine tasks, such as medical diagnostics, translation work, and driving a car (Brynjolfsson and McAfee, 2014). As a result, Frey and Osborne (2017) estimate that 47 per cent of US employment is at 'high risk' of automation over the forthcoming decades, with a substantial share falling into *non-tradable* sectors of the economy, to which most workers have already reallocated: 98 per cent of total US employment growth between 1990 and 2008 accrued in sectors where jobs are unaffected by import competition (Spence and Hlatshwayo, 2012). While this shields many workers from the adverse impacts of trade (Acemoglu *et al.*, 2016), it does not constitute a safeguard against automation—indeed, as President Obama noted when leaving office: 'The next wave of economic dislocations won't come from overseas. It will come from the relentless pace of automation that makes a lot of good, middle-class jobs obsolete.'

Of course, over the very long run automation has *always* been an engine of comfort and prosperity. After six decades of stagnant wage growth during the British Industrial Revolution, ordinary workers eventually became the prime beneficiaries of automation as they adapted and acquired new skills (Galor and Moav, 2004; Bessen, 2015). Between 1840 and

[15] Most citizens lacked voting rights, for which property ownership remained a prerequisite; even with the Reform Acts of 1832 and 1867.

[16] Cited in Curtis (1983).

[17] As forcefully argued by Crafts (2015), 'fears about long-term "secular stagnation", based on the end of innovation as we have known it, seem overdone. The problem is much more likely to be the factor-saving bias of technological progress based on computerization of jobs than a drying-up of productivity growth.'

1900, real wages in Britain grew by 123 per cent, considerably faster than output per worker (Allen, 2009). Could history repeat itself? Perhaps so; so far, the economic trajectories of the age of automation closely resembles those of the British Industrial Revolution. But any future benefits from automation hinge upon its politics. To avoid further populist rebellion and a looming backlash against technology itself, governments must find ways of making the benefits from automation more widely shared.

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