Voting Machines

Automation and Associated Changes in American Voting Patterns

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Summary

This paper investigates whether politicians of the radical-right will continue to benefit electorally, as they currently do, from workers whose jobs are at risk of being automated as current trends see more and more jobs replaced by machines. I address this question using two approaches. Looking at the 2020 presidential election I first examine whether, once in office, a radical-right politician, Donald Trump, continued to command the support of those voters affected by automation who helped secure his election in 2016, given that he failed to meaningfully address the continued destruction of jobs and downward economic mobility that automation has been causing for the last four decades in the United States. Second, I use the candidacy of Bernie Sanders to examine whether politicians who are not of the radical right, but who are perceived by voters affected by automation risk as offering viable alternatives to the status quo, can attract these voters' support.

This approach expands on previous work on the subject notably that of Frey et al (2018), whose methodology I use, and to a lesser extent Im et al (2019). Both authors solely focused on the radical-right and use traditional political distinctions. I instead identify a political phenomenon I term "anti-status quo" politicians, who are characterised not by political ideology but by their proposals to significantly change the political status, and by the fact that their promised radical changes are perceived as credible. While the term "anti-status quo" can be used to describe the radical right, I argue it can also be applied to a wide variety of other politicians and political parties, including a self-styled Democratic Socialist like Sanders.

After first defining automation and illustrating its effects and mechanics in both historical modern contexts, I test my hypothesis by regressing changes in the vote share for Donald Trump and Bernie Sanders against changes in the percentage of the labour market composed of jobs at risk of automation at the county level, along with a robust series of controls. Theoretical grounding is established to support my argument that a fall in support for Trump among voters affected by automation is a result of their disillusionment with his failure to deliver for them while he was in office and that support for Sanders is indicative that voters in recent elections are attracted to a variety of kinds of radical change, not only the kind offered by the policies of the radical right.

The methodology is applied to Trump's 2016 presidential campaign to establish that the results used coheres with the previous literature, which already supports the view that Trump won a significant margin of the votes cast by those who were exposed to automation risk. Trump's performance in 2020 is then analysed; it is found that support for him essentially collapsed among these voters, suggesting support for the radical right is conditional on the credibility of their candidates. The results of Bernie Sanders' performance in the 2020 primaries are found to be less conclusive. While there is a correlation between support for his campaign and counties with higher percentages of automatable jobs in their labour markets, these results are not large enough to state there is a meaningful link

between support for Sanders' particular brand of radicalism and voters whose jobs may be replaced by machines, and concerns are raised about the regressions' robustness. Nonetheless, the results are such that the idea that automation-related disaffection is exploitable by a variety of political platforms cannot be ruled out; further investigation is called for.

Acknowledgements

Neither this dissertation nor the rest of this master's degree would have been possible with the considerable amount of support I received. So my deepest thanks to the staff and students of Trinity's Economics M.Sc., who faced what came with determination and good cheer, my supervisor, Selim, for his invaluable advice and understanding, Trish, who believed I could do it, and Adam and Tobias for their encouragement and for spending far too long on video calls with too little whiskey drunk. Finally, to all my friends, but especially my family, for putting up with and supporting me through what was, by any metric, a very strange year.

1. Introduction

On the 8th of November 2016, Donald J. Trump was elected president of the United States. On the 3rd of November 2020, Trump lost his re-election bid to Joseph R. Biden Jr. Trump's four-year presidency was notable for a great number of reasons, but in addition to these it was bookended by two singular advances in computing. In March 2016, a computer programme named AlphaGo defeated 9 *dan* Korean Go player Lee Sedol 4 games to 1: a feat that had previously been believed to be considerably more difficult that teaching a computer to play chess (Good, 1965). In November the same company, a Google subsidiary called Deepmind, demonstrated a programme called AlphaFold which was capable of predicting protein structures, an achievement that was hailed "transformational" to the future of all biological sciences on the pages of *Nature* (Callaway, 2020).

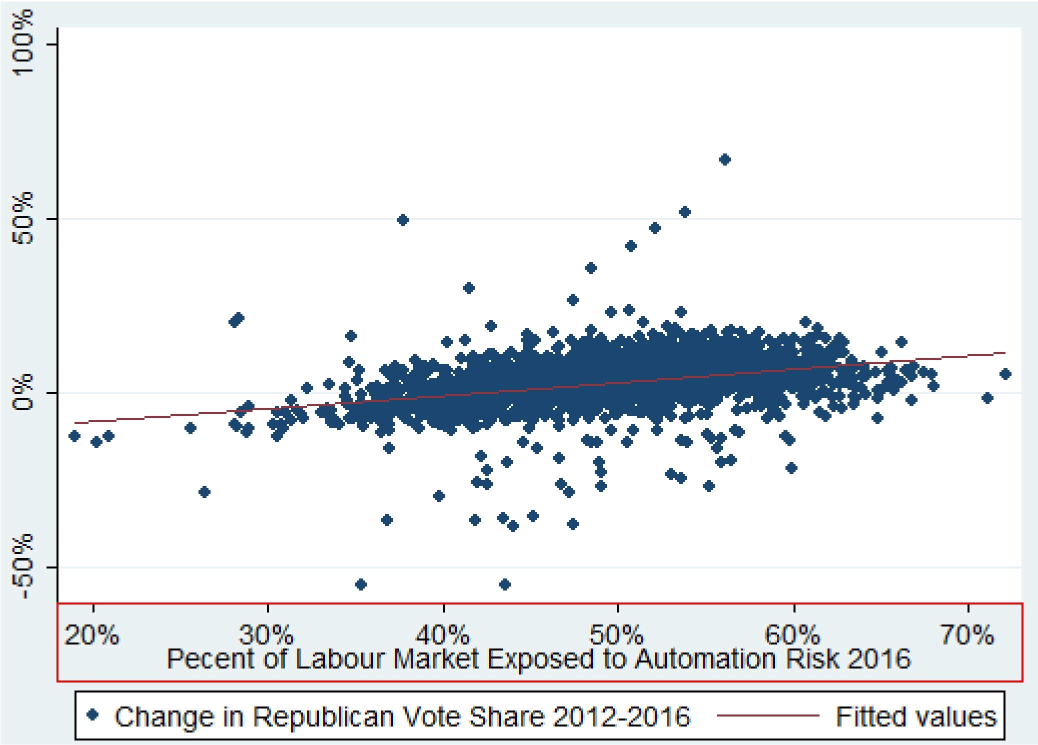
While remarkable in themselves, these breakthroughs are just the most recent in a more than forty-year long trend in computer driven automation. Such advances are often described as progress, but economically, many of them have come at a cost to workers who are replaced in their jobs by machines (Autor & Dorn, 2013). Further, such workers have frequently found no equivalent employment available to them (Jaimovich & Siu, 2012), forcing them down the income distribution into lower paid work or out of the workforce altogether.

Those directedly effected by automation, along with those whose jobs are currently at risk from it are not only workers; they are also voters. Recent studies have found a link between those voters whose jobs are exposed to automation risk and political backlash; evidence has been found of such voters turning to parties of the radical-right throughout Europe as well as to Donald Trump in the United States.

Will the radical-right continue to rise as more jobs become replicable by machines? I seek to investigate this question using two approaches. First is to examine whether, once in office, the radical-right can continue to command the support of those voters affected by automation if such politicians fail to meaningfully address these voters' concerns. Second is to examine if other political actors apart from the radical right are perceived by voters as offering viable alternatives to those affected by advances in automation. This expands on previous work on the subject notably that of Frey et al (2018) and to a lesser extent Im et al (2019) who solely focused on the radical right, and whose use of traditional political distinctions does not account for the fact that radicalism can be compatible with a plethora of policy platforms.

After first defining automation and illustrating its effects and mechanics in both historical modern contexts, I test my hypothesis by borrowing the methodology of Frey et al (2018) to examine the American General Elections of 2020. Changes in the vote share for Donald Trump and Bernie Sanders were regressed against changes in the percentage of the labour market composed of jobs at risk of automation at the county level, along with a robust series of controls. Theoretical grounding is established to support my argument that a fall in support for Trump among voters affected by automation is a result of their disillusionment with his failure to deliver for them during his presidential term and that support for Sanders is indicative that voters in recent elections are attracted to a variety of kinds of radical change, not only the kind offered by the policies of the radical right.

Figure 1. Support for Trump versus Automation Risk in 2016



The methodology is applied to Trump's 2016 presidential campaign to establish that the results used coheres with the previous literature, which already supports the view that Trump won a significant margin of the votes cast by those who were exposed to automation risk (see figure 1 for a graphical representation of this). Trump's performance in 2020 is then analysed; it is found that support for him essentially collapsed among these voters, suggesting support for the radical right is conditional on the credibility of their candidates. The results of Bernie Sanders' performance in the 2020 primaries are found to be less conclusive. While there is a correlation between support for his campaign and counties with higher percentages of automatable jobs in their labour markets, these results are not large enough to state there is a meaningful link between support for Sanders' particular brand of radicalism and voters whose jobs may be replaced by machines, and concerns are raised about the regressions' robustness. Nonetheless, the results are such that the idea that automation-related disaffection is exploitable by a variety of political platforms cannot be ruled out; further investigation is called for. I conclude with a brief discussion of what my findings mean in the context of probable future trends in automation.

The rest of the paper is structured as follows: Section 2 gives a literature review of the subject and a theoretical foundation for the paper. Section 3 outlines the data that is used and section 4 details the paper's methodology. Section 5 presents the paper's results and features analysis of their implications. Section 6 contains further discussion of the robustness and implications of the results and section 7 concludes.

2. Literature Review and Theoretical Foundation

Why Voters care about Machines

Accounting for popular dissatisfaction with automation can be a challenge for many economic models, as they tend to classify technological progress as a good thing. Neoclassical theory in particular treats automation as a Pareto improvement: positing that even if people are put out of work by machines, the growth they provide will result in replacement jobs for all that are better paid (Frey et al, 2018). The historical record has, however, seemingly taken umbrage with this view at various points. Schumpeter's ideal of creative destruction is best understood by remembering that if a job is replaced by a machine, while a new job may be made available, there is little guarantee that it will be for workers with the same skillset. Thus, those that the machines make redundant face a real risk of only being able to find lower paying work or perhaps being unable to find work at all.

Consider the following thought experiment: Imagine an economy where only three people are of interest to us: two manual labourers and an engineer. The labourers work on a farm and the engineer tinkers with machines in her shed. Eventually, the engineer invents a combine harvester, which is a cheaper way to farm that using manual labour, so one of the labourers loses his job. However, the additional productivity gains from the farm now leads to a situation whereby the first labourer has enough income to demand an additional slew of goods and services. The redundant labourer gets a better paid job in an office of a company that sells to the now wealthier farmhand. The inventor prospers from the rents she collects on her patent, and everyone is materially better off.

Now consider a modern version, where we focus on two middle income workers and another inventor. This time the inventor is a computer scientist who develops an algorithm to automate the job of one or both of the office workers. While this makes her rich, the algorithm is widely deployable meaning offices aren't hiring new workers. Though additional demand is generated by the offices' productivity gains, this only results in additional jobs that are difficult to automate. Not qualifying for roles that require experience or advanced degrees, these men will only be able to find work in a subset of jobs that are difficult to automate. Unfortunately for them, such roles tend to be lower paid service sector work, such as bicycle couriers and waiters. While this is problematic from the perspective of the wider economy, as these workers now generate less demand due to their more limited means, it is especially problematic from the perspective of the workers who are now markedly poorer.

Thus, we can see that economic growth, and the technological change that helps drive it, frequently negatively impacts segments of the workforce. In addition to the aforementioned lower wages and joblessness, the "losers" of automation may be forced to migrate to secure work, accept work with considerably less favourable conditions or in less favourable environments, or just generally have their sense of dignity and identity challenged by the disruption and precarity that automation can cause. Understandably, such workers, along with their families and communities, can get pretty upset about such effects of automation.

Even though such political discontent does not primarily express itself in markets, it is definitely linked to economic policies and outcomes, and invariably becomes something that national politics addresses in some form. So, even though it is possible to think of changes in production technology and Pareto superior, advances rarely work out this way in practice. Excepting scenarios which are logically possible, however unlikely, that all participants benefit from these outcomes, the economic actors whose lot is worsened by automation will be prone to resist and demand restitution for its ill effects through non-market means, particularly political activism (Mokyr, 1998).

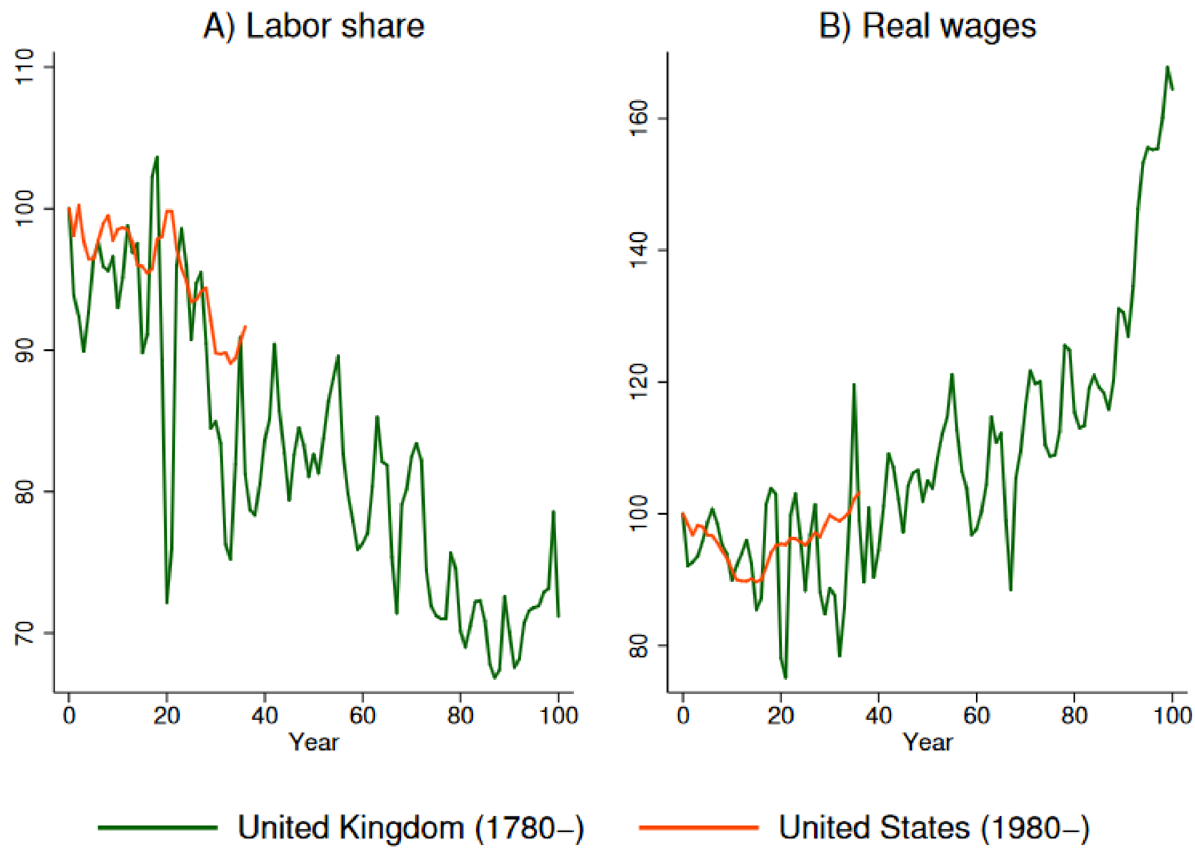
That said, it has been made clear that the overall effectiveness of any resistance to automation will be proportional to the share of those whose who receive economic gain. The 20th century saw the professions of typists, telephone operators, and railroad telegraphers (along with the men who shovelled coal into the engines of steam trains) rendered obsolete. However, the developed world also saw a marked rise in what might be termed "middle-class jobs", typified by the sort of professions like doctors, lawyers, engineers, and accountants, as well as administrative and managerial office work (Gordon, 2016, Lindert and Williamson, 2016). Thus, the median worker became more affluent, and automation was treated with indifference or actively welcomed by the majority. However, as mentioned above, there was no guarantee that automation would continue to produce such happy results, and, as a matter of fact, it has not.

A Potted History of Automation

Historical evidence of the dissatisfaction that can accompany automation can been seen in England during the Industrial Revolution. Older artisans, particularly skilled weavers, were made redundant by machines. Adult male workers lost out and the percentage of the workforce comprised of children, a cheaper source of labour willing to learn new skills and suffer worse conditions, expanded rapidly. Approximately half of the workforce employed in textiles in 1830's England were children (Tuttle, 1999). Frey et al (2018) note that over the initial sixty years of the Industrial Revolution, the average English worker saw no benefit from automation in his pocket. Though output expanded, real wages were stagnant, meaning that there was a steep fall in the share of national income attributable to labour. The authors additionally find that trajectories of the American economy over the last 40 years almost exactly mirror the first four decades of the Industrial Revolution in Britain (Figure 2).

Frey et al also find a link between trades affected by automation and poverty. This was particularly notable for weavers, who saw the handloom replaced by the power-loom which drove many of them into, at best, worse paying agricultural work or, at worst, penury (ibid). The political consequences of this were dramatic; affected workers frequently clashed violently with forces of the British government. Former workers burned down factories, notably a steam-powered sawmill in Limehouse in 1768 and a factory using power looms in Lancashire in 1772. The workers were ultimately unsuccessful; happy with the benefits of automation to their trade balance and indifferent to the lot of those it impoverished, the government sent an army 12,000 strong to quell the Luddite risings of 1811-1813, a larger army than was fielded against even Napoleon in the Peninsula War of 1808 (Berg, 1982; Frey et al, 2018; Mokyr, 1990, Mantoux 2013). In short, the experience of automation during the Industrial Revolution produced winners and losers, and the losers were very, very angry at the machines and those who profited from them.

Figure 2. Comparison of Automation during the Industrial Revolution and the Modern Era.



This figure shows the labour share of national income (panel A) and the trajectories of real wages (panel B) in the United Kingdom between 1780-1880 and in the United States between 1980-2015 (Frey et al, 2018).

For the last 42 years, machines have been replacing workers on assembly lines, secretaries in offices, paralegals in law firms, and even workers who used to operate the machines for a living (Autor et al, 2003). Over this time entirely new occupations have come into existence, notably in the computer industry, such as software engineers and data scientists, and formerly niche tasks such as graphic designers and audio-visual editors have become considerably more widespread (Berger and Frey, 2016). However, these sets of jobs require different sets of skills, and as those without a third level education, those who lose out to automation in factories and customer support centres cannot simply transition to being management consultants or full stack developers; as such they face having to move to lower waged work or even unemployment (Cortes et al, 2016).

The US economy has grown thirty-six of the forty-one years since 1979 (World Bank, 2021). However, between 1979 and 2013 productivity grew at eight times the rate of hourly wages; some 64.9% compared to an 8.2% growth in hourly wage for 80% of Americans (Bivens et al., 2014). Hence, the wages of most US workers stagnated, or even declined. Excepting for a brief period at the end of the 1990s, middle income workers did not see any wages increases or even had their wages fall. Workers on low wages saw their incomes fall by 5%. This trend accelerated after the beginning of the 21st century; hourly wages fell for the lowest earning 30% of the population and were stagnant for the next 40%.

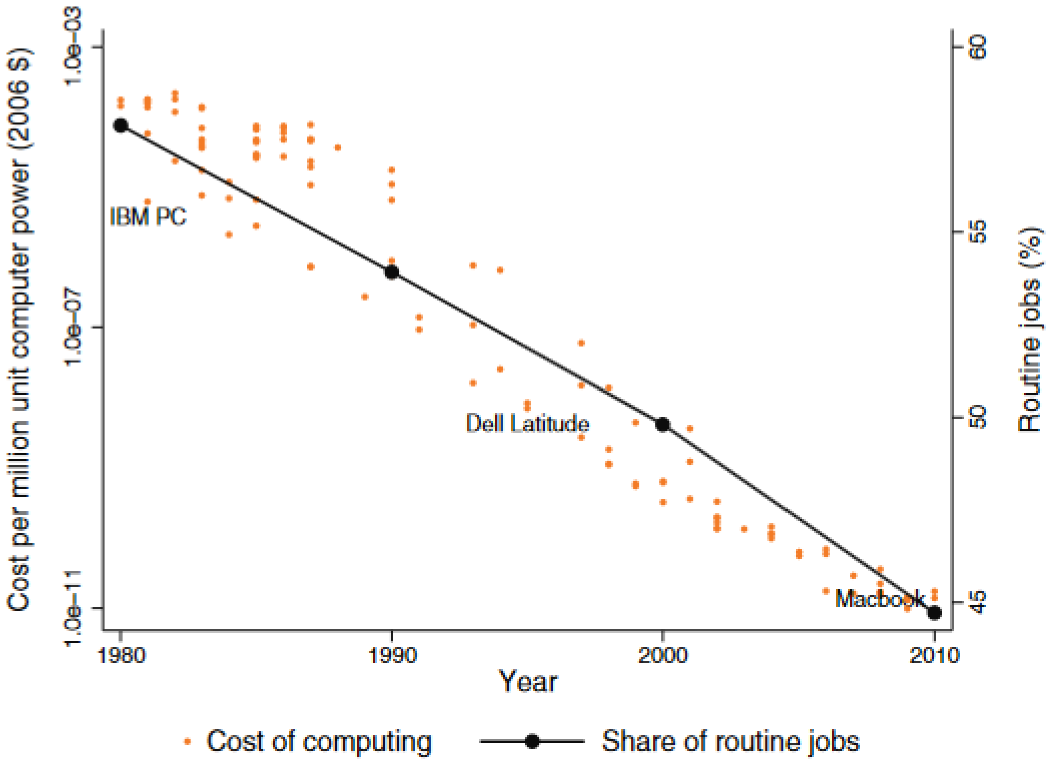
Where have the gains from this period of growth gone? Most of it has been accrued by the capital and its holders. Over the 1979 to 2013 period, the top 1% of earners experienced a cumulative average increase in their annual wages of approximately 153.6% (Bivens et al., 2014). Additionally, while the share of national income in the US accounted for by labour stood at approximately 64% during the period of 1945 to the late 1970’s, from the early 1980’s it began falling continually, reaching its lowest point in the aftermath of the 2008 financial crisis only rebounding to a level approximately 6% lower than it was during the first four decades after World War II (Frey et al, 2018).

The size of this distributional change is stark. One estimate posits that were the income distribution of 1979 to hold today, the bottom 80% of American earners would see their annual income rise by an average of $11,000, while the top 1% of earners would collectively lose $1 trillion dollars in annual income (Summers, 2015).

There is a large and growing body of work that points the blame for these shifts in inequality on automation. Specifically, it argues that automation is one of the primary factors causing the changes in income shares along the occupational wage distribution (Autor et al., 2003; Autor and Dorn, 2013; Graetz and Michaels, 2015; Michaels et al., 2014), as well as from labour and owners of capital (Karabarbounis and Neiman, 2013). These papers play down alternative explanations which emphasise manufacturing decline, falling levels of union membership, and globalised immigration as causes for changes in national income distribution.

How does this work in practice? Since the early 1980's, there has been a trillion-fold decline in the price of computing[1] (Nordhaus, 2007, Figure 3) While it can be empirically challenging to identify which categories of workers have lost out to automation, a number of studies notably Autor et al (2013) and Jaimovich and Siu (2012) have pointed to so called "routine occupations", as those being most at risk of automation (additional work on this has been done by Acemoglu and Autor, 2011; Autor and Dorn, 2013; Goos and Manning, 2011; Goos et al, 2009.). Such routine jobs include machine operators, assembly workers, bookkeepers, paralegals, and secretaries.

Figure 3. Computers and the Decline of Routine Jobs in the United States, 1980-2010.



This figure outlines the dramatic decline in the costs of computing for a variety of models launched between 1980 and 2010 and the decline in the share of the US labour market composed of routine jobs over the same period (Frey et al, 2010)

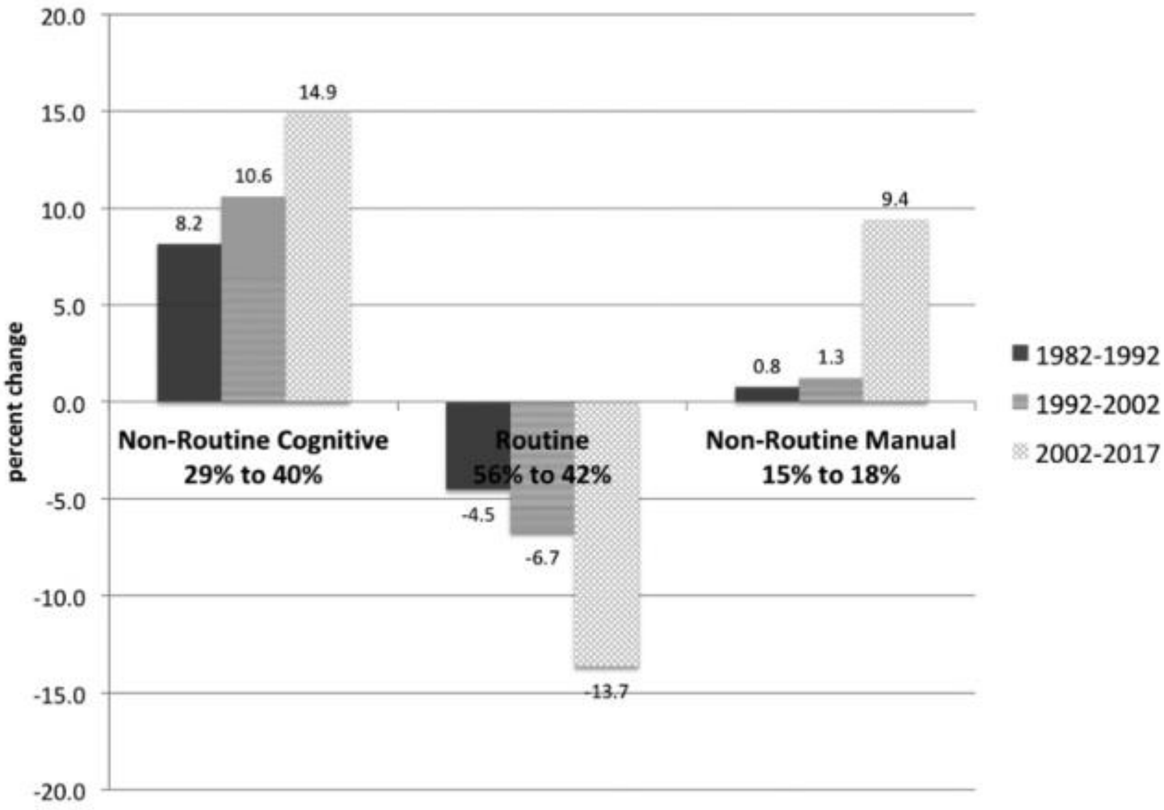
The distinction between routine and non-routine jobs is based on Jaimovich and Siu (2012). Routine jobs are those comprising of tasks that can be "summarised as a relatively small set of specific activities accomplished by following well-defined instructions and procedures" (ibid; 133). Jobs that require creativity, judgement, problem solving, or complex human interaction are considered non-routine. Routine tasks are relatively more susceptible to automation, whereas non-routine tasks at

[1] This is described by Moore's Law; a phenomenon whereby the number of transistors that can be placed on a microchip approximately double every 18 months, thereby functionally halving the price of computing every year and a half (Moore, 1965).

present are quite difficult to automate (Agrawal et al, 2018). Routine jobs can be manual in nature, like those of a mechanic, dressmaker, assembly line worker, or meat processing worker, or cognitive such as those of bank clerks, customer support staff, travel agents or secretaries.

Routine jobs, both cognitive and manual tend to be found in the middle of the income distribution (Goos et al., 2014; and Jaimovich and Siu, 2012). Because of this both cognitive and manual routine tasks are grouped together, and thereafter simply referred to as routine tasks. Though it might seem counter-intuitive to some that many non-routine tasks are lower paid that routine ones, plenty of unskilled labour is comprised of tasks that require the difficult-to-automate skills outlined above, such as waiters and bicycle couriers. Obviously, there are also many highly paid non-routine jobs, such as managers, doctors, scientists, and graphic designers.

Figure 4. Percent change in Employment Share by Occupation Group



(Jaimovich and Siu, 2012)

The percentage of the US labour market composed of routine jobs has been in decline since the 1980s (Figure 4), however it has not fallen at a steady rate. The speed of automation has increased in recent years, most notably in the immediate aftermath of the 2008 financial crisis (Figure 5). Although low and high skilled employment recovered in the aftermath of the crisis, the recovery for middle income, routine employment could best be described as “jobless” i.e., while the tasks that constituted these job that were lost in 2008 were being performed for businesses once again, they were being performed by machines or computer programmes rather than human beings. Technology seems to have been the culprit for this, as no jobless recovery has been observed prior to the widespread adoption of computers (Jaimovich and Siu, 2012).

Figure 5. Employment in Occupations 1980-2017

Grey lines denote periods of recession (Jaimovich and Siu, 2012).

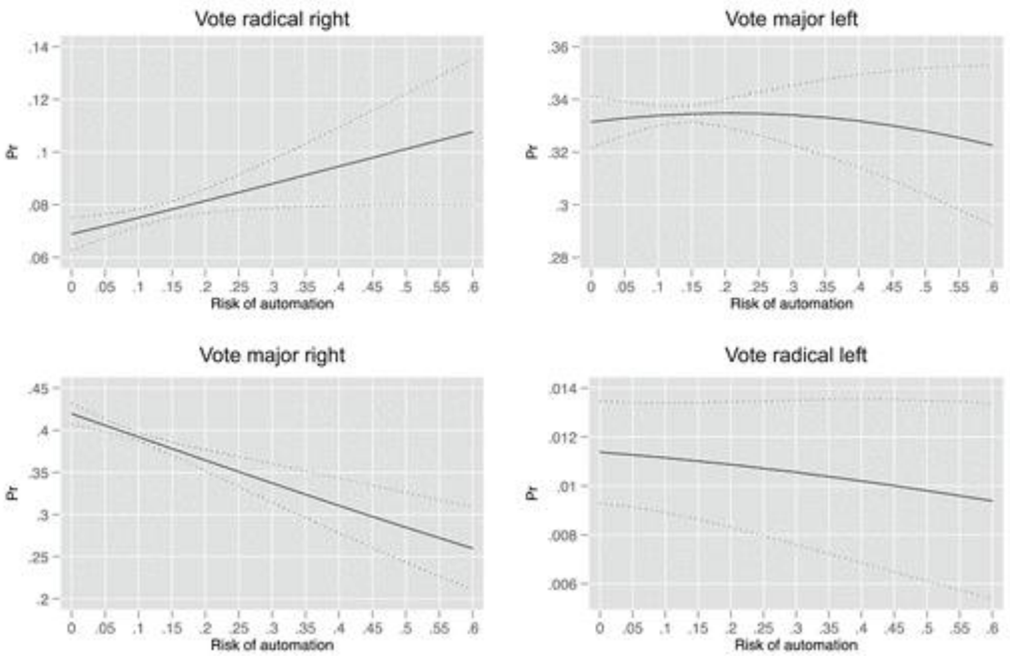
The effect of this seems to have been to force those who had formerly held some form of routine employment to either take up some form of non-routine manual job or to simply leave them unemployed (Cortes et al., 2016). The disappearance of routine jobs has coincided with a structural shift in the US labour market with workers frequently entering low-income service occupations (Autor and Dorn, 2013), which require the use of judgement and physicality making them more difficult to automate (Acemoglu and Autor, 2011; Autor et al. 2003; Goos and Manning, 2007; Goos et al. 2009). There is a direct link between these changes; manual non-routine jobs like carers, cleaners, and bike curriers tend to be found at the bottom of the wage distribution, whereas routine occupations such as factory workers, miners, and secretaries, tend to be mid-waged roles (Autor and Dorn,2013; Goos and Manning, 2007). We can see from this that the automation of routine jobs has effectively served to impoverish those it has affected.

Beyond Left and Right: Populism (and the lack thereof) in modern politics

Given, then, that there are a considerable number of workers in the developed world who stand to lose out, or have lost out to automation, the question is then what do they do about it? As mentioned, political activism is a route with considerable appeal and voting is a low-cost way to make one's concerns know to the representatives who govern one's country.

As mentioned, there is a body of evidence outlining that politicians of the radical-right have attracted the votes of workers whose jobs are at risk of being automated in recent years. As the results this paper replicates from Frey et al (2018) show, US workers whose jobs were at risk of automation accounted for a considerable percentage of Donald Trump's overall vote share in 2016 (see Figure 1 and Table 1). Im et al (2019) find similar phenomena have been occurring in recent European general elections. They argue that parties of the radical-right were, at the time of writing, "the most electorally dynamic in Europe", but also the only non-mainstream parties to have put forward the issue of automation risk and whose rhetoric harkens back to a nostalgic myth of the past *pace* European parties of the far-left[2] who defend technological progress (Gest et al., 2017; Steenvoorden and Harteveld, 2018). The authors support this empirically, noting that as the risk of automation rises from 0 to 0.6, a 3.92% associated increase in probability of voting for radical right parties is seen. They find the same shift associated with a 16% decrease in votes for established right-wing parties, and no significant effect associated with voting for the parties of the centre or far left, or otherwise (Figure 6).

Figure 6. Relationship between vote probability and risk of automation



Im et al (2019)[3]

The central thesis of this paper is that while Frey et al and Im et al's analysis is good, they have failed to understand the entirely to the political phenomenon they identified. Both papers' claim that voters exposed to automation risk opt for radical change. While Frey et al believe that voters affected by automation will opt for "radical change" (2018) they only speak of radical change in the context of the

[2] Here I use the term far-left rather than Im et al's stated term radical-left. This is because I do not believe all self-styled radical-left wing parties in Europe, particularly long-established parties of the far-left, are seen as presenting a credible change to the status quo. See appendix for further details.
[3] Sample countries observed are Austria, Belgium, Denmark, Finland, France, Germany, Italy, the Netherlands, Norway, Sweden and the UK.

Trump candidacy. Im et al investigate parties of the radical left as well, but only find a connection between exposure to automation risk and increases in votes for radical right parties.

Here, I believe both papers have made an unwarranted logical leap. This paper contends that the germane level of analysis is that of radical change, not the radical right (or indeed radical left, centre, or any other political ideology). Voters whose jobs are at risk of being automated face precarity, downward mobility, all too frequently the threat or reality of poverty. My theory is such voters' primary concern is that these circumstances change, and not, on average, the precise nature this change will take. Such voters are posited to believe that conventional politics has failed them; many will have formerly voted for established parties, but now feel that such parties have let them down, either due to ideology, incompetence, or inability. The two things that *are* important to these voters is that a politician or politicians offer to change the status quo that threatens their livelihoods, and that those politicians and their promised change are perceived as credible.

I term politicians or parties that meet these criteria "anti-status quo." Those who fall under this term are all necessarily perceived by voters to be a meaningful break from "politics as usual," but beyond this they may have little or nothing else in common. Their credibility can derive from voters believing that their policy platform will allow things to meaningfully change, or it can derive from the personal charisma of a particular political leader. Such parities may promise to change the foundations of the state, or they may simply promise to make what already exists work for once. They may be of the left, right, or centre; pluralistic and liberal or authoritarian and conservative. As such, it is not possible to group these parties using traditional political distinctions; anti-status quo parties certainly include the radical right, but also the nationalistic centre, and the liberal left. Their commonality is that within their own political context is that there is a credible perception that a vote for them is a vote for a radical change to the status quo.

To find concrete examples, I turn to recent European elections. As mentioned, parties of the radical right, like France's *Front National*, the UK's UKIP, Italy's *Legue* have benefited considerably from automation risk in recent elections (Im et al, 2019). However, my conjecture is that there are quite a few other, ostensibly politically disparate parties that have benefited from the same phenomena. An example of one such party is *Movimentio 5 Stelle* in Italy. In many ways a party of the left, advocating a form of Universal Basic Income, direct democracy, and nominally radically pro-environment policies (Gerbaudo, 2014). They are also considerably less pro-EU than the traditional parties of the Italian left and centre EFDD group in the European Parliament, a group that also contained UKIP. All of this represented a considerable break with the Italian political status quo.

Another example of an anti-status quo party would be is the Scottish National Party. Economically ranging between right and left (the party members hold a wide variety of economic ideologies (Millar 2016)) the party is social liberal, in favour of multiculturalism, and advocates military neutrality and nuclear disarmament (Mitchell, 1996). Nonetheless, by advocating Scottish independence, it is perceived to be a party that represents a credible break with the status quo. The party shares many similarities with the UK Labour party on economic and social issues, but nonetheless supplanted them electorally during the financial crisis, and have continued to wax electorally since then. This could be accounted for in part by the aforementioned economic trends in the developed world (Southern Scotland, the area of the country with the largest population, was the UK's poorest region as of December 2020 (Europa.eu, 2020)), with Scottish voters feeling that successive Governments in Westminster have failed to deliver for them, so radical change is required.

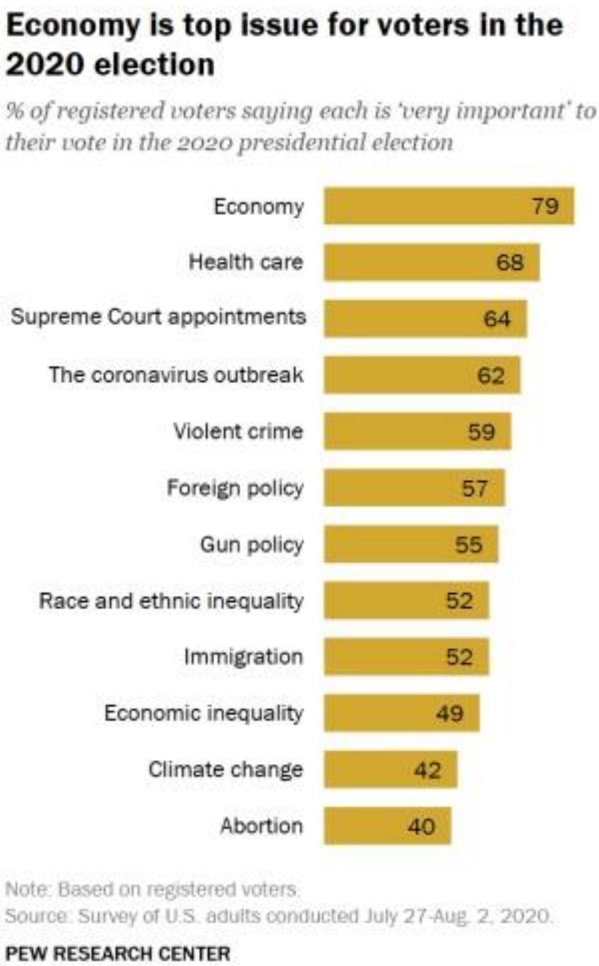
Automation and American Politics

There are more examples of anti-status quo parties throughout Europe, however, this paper concentrates instead on the recent US presidential election of 2020 for five reasons, which will be enumerated below.

First, it is comparatively straightforward to define the political status quo in the US. The essayist and commentator Gore Vidal frequently remarked that there is only one party in the United States, and it has two wings: Republican and Democrat[4]. While it may be a mischaracterisation to insist, as Vidal did, that there is essentially no difference between the two parties, as a point of fact both have presided over the secular trend in automation described above.

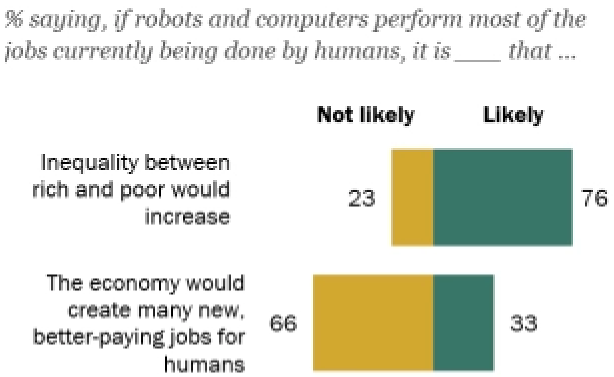
[4] While there are other parties in the United States, such as the Libertarian Party and the Greens, they commanded a relatively negligible percentage of the vote share in presidential elections and so are discounted from the analysis.

Figure 7.



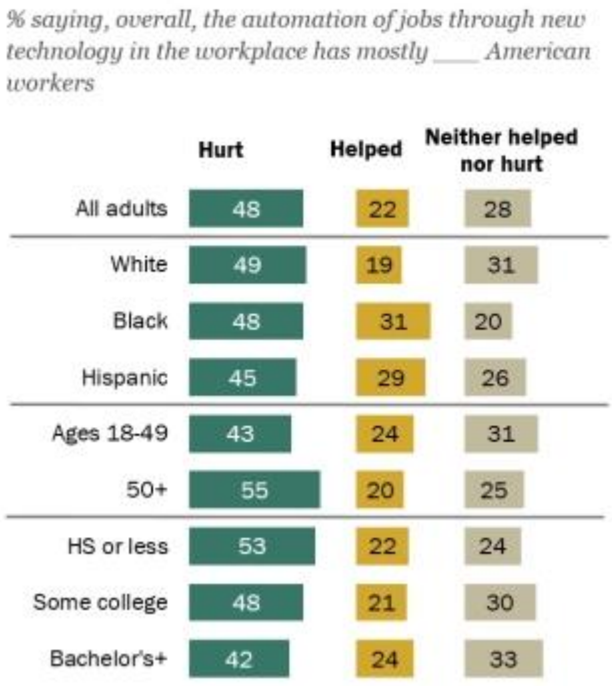
Second, on account of the clearly defined political status quo, it is also comparatively simple to define the political candidates who represent a break with the political status quo. In the past five years, two such politicians have emerged as serious contenders for the Presidency, Bernard "Bernie" Sanders, and Donald J. Trump, with the latter being elected the 45th president of the United States in 2016. Sanders promised nationalised health care, restructuring of the banking industry, and to directly tax personal and corporate wealth to a hitherto unseen extent (Ebeling, 2015). Trump's radicalism rested in part on his personal appeal, being widely perceived as a political outsider who would not allow himself to be constrained by conventions or protocols to a notably greater extent than any other politician; 82% of voters believed that Trump was the candidate for change in the 2016 general election, according to the exit polls (Frey et al, 2018). Policy-wise, Trump promised to slash immigration drastically, and take a far more confrontational approach to trade with China (Bloomberg, 2021). Both candidates were sceptical of foreign military intervention and the benefits to the US of international trade agreements such as NAFTA and TIPP, arguing for various forms of protection for US industries (Yarvin, 2017).

Figure 8a.



Third, it is reasonable to assume that automation was a factor in voters' minds in the 2020 election. While polls did not specifically point to automation as a concern for voters, they nonetheless listed the economy as a concern above everything else, even the candidates handling of the pandemic (Pew 2020, Figure 7), which this paper assumes to encompass voters' concerns about automation. Automation was given a higher profile in the 2020 election after being raised as a tentpole issue by Andrew Yang in the democratic primaries (Yang 2019), and the Biden campaign featured specific policy proposals to train and reskill the workforce to adapt to the automation caused by AI. Biden himself gave a speech where he recalled talking to old schoolmates about automation, one of whom worked as a truck driver and noted that he was "scared to death; they're scared to death," of self-driving trucks. (Thibodeua, 2020). As well as being aware of automation, there is evidence that voters were sceptical of its economic effects; surveys suggest most Americans believe automation has done more harm than good and that further increases in automation will lead to more income inequality (Pew 2019, Figure 8).

Figure 8b.



Fourth, as outlined above, the anti-status quo candidates have distinct policy platforms, as well as personal styles, and come from markedly different political traditions; Trump falls on the radical right, and Sanders is a self-described Democratic-Socialist (Ebeling, 2015). This enables an investigation into whether anti-status quo candidates who are not on the radical right can appeal to voters exposed to automation risk.

Finally, given the fact of Trump's presidency, the US allow one to examine what happens when a candidate who ran as a credible alternative to the status quo is successfully elected, and therefore become representative of the status quo upon re-election. Since the secular trends in automation persist and indeed increased during the Trump presidency (Agrawal et al, 2018) I seek to investigate whether voters exposed to automation risk abandoned Trump in 2020 given that he failed to address the issues that caused them to vote for him in 2016.

Based on the hypothesis that workers exposed to automation will be attracted to credible promises of radical change from a variety of divergent policy platforms, this paper explores the relationship between the support for anti-status quo presidential candidates and the share of routine jobs across electoral districts. This approach exploits the variation of the exposure of workers to automation across different regions of the US; a growing body of evidence suggests that different parts of the US have experienced varying trends in their economic welfare as a result of past automation. Since the advent of modern automation in the 1980s, areas with abundant human capital have experienced the creation of new jobs, particularly in those areas related to the production, use, and maintenance of computers systems (Lin, 2011; Berger and Frey, 2016) while locations with a greater share of routine employment have seen automation destroy workers' jobs (Autor and Dorn, 2013).

3. Data

The analysis of all votes was performed at the county level. To identify the labour market and demographic composition of each county, I rely on data from the 2015 and 2019 American Community Surveys (ASC), which proves a one percent sample of each county' population which can be matched to electoral results (Ruggles et al, 2017). The approach details the voting outcomes for some 3,107 counties across the continental United States[5]. The ACS divides the labour market into five broad classes of occupations: (1) Management, Business, Science, and Arts occupations, (2) Service occupations, (3) Sales and Office occupations, (4) Natural Resources, Construction, and Maintenance occupations, and (5) Production, Transportation, and Material Moving occupations. In line with the definitions provided in Jaimovich and Siu (2012) and Autor and Dorn (2013) this paper classifies the latter three occupational categories as consisting of "routine jobs", and therefore being susceptible to automation. The sum of the percentages of the labour market, comprised of Sales and Office occupations, Natural Resources, Construction, and Maintenance occupations, and Production, Transportation, and Material moving occupations, is then computed to generate a variable measuring the percentage of the labour market at risk of automation in a given election year.

To investigate the link between voters' differing levels of exposure to automation and their propensity to vote for an anti-status quo candidate, county level voting results outcomes, sourced from David Leip's *Atlas of US Elections* (Leip, 2021), was used to construct variables measuring the difference in Republican vote-share between the 2020 and 2016 elections and the 2016 and 2012 elections as well as the difference in vote-share received by Sanders in the 2020 and 2016 primaries.

4. Methodology

As Figure 1 shows, there is a positive relationship between and support for Trump in 2016 and exposure to automation risk. While this correlation is suggestive of a meaningful relationship in order to substantiate this, it is necessary to control for a variety of factor. Borrowing the methodology of Frey et al (2018) the following regression is constructed:

[5] Analysis of the Presidential Elections excludes the states of Hawaii and Alaska due to geographic discontinuity. Analysis of the Democratic Primaries additionally excludes the District of Columbia and Puerto Rico for coherence with the results of the General Election, as well as Kansas, Maine, Minnesota, and North Dakota due to data limitations.

$$\Delta V_c = \alpha + \delta A_c + \theta X_c + \gamma_s + e_c$$

where the dependent variable, ΔV_c, is the change in the Republican vote share between the 2012 and the 2016 general election in a given county, c. The variable of interest, A_c, denotes the percentage of a county's labour market that is composed of jobs susceptible to automation. X_c is a matrix of control variables, including county level labour market and demographic characteristics, further outlined below. Finally, γ_s, a variable for state fixed effects, included to examine whether a link between support for Trump and automation risk exists when factoring out characteristics particular to each state.

5. <u>Results</u>

<u>TRUMP 2016</u>

Table 1 presents a summary of OLS estimates of the above regression equation, and documents a large and highly significant correlation between increases in Republican vote share and exposure to automation risk in 2016:

TABLE 1

	Outcome: Change in Republican vote share General Election 2016 (Trump) vs. 2012 (Romney)				
	(1)	(2)	(3)	(4)	(5)
Change in Automation Risk	38.11048***	38.2164***	31.41949***	6.5098***	9.46298***
Robust Standard Error	(1.99867)	(2.01053)	(1.98358)	(2.9821)	(2.95471)
Labour Market Controls?	No	Yes	Yes	Yes	Yes
Demographic Controls?	No	No	Yes	Yes	Yes
Education Controls?	No	No	No	Yes	Yes
State Fixed Effects?	No	No	No	No	Yes
R^2	0.1430	0.1465	0.2908	0.3624	0.5662
Number of Observations	3,107	3,107	3,107	3,107	3,107

*** p < 0.01, ** p < 0.05, * p < 0.1 All coefficients denote a percentage change in the popular vote.

The table shows that the share of routine employment had sizable explanatory power in 2016, suggesting that an increase of 1% in the share of the labour market composed of routine jobs was associated with a 38% in support for the Donal Trump compared to what Mitt Romney received in 2012. Furthermore, the figure accounts for some 14% of the variance in the change in Republican vote share. Combined, these figures suggest that not only was automation an important issue to many, but that it played a considerable part in Trump's electoral success.

Since the distribution of jobs at risk of automation is almost certainly correlated with a number of factors that may have a causal impact on the relationship seen in regression (1) it is necessary to control for these factors to ensure that this relationship holds up.

Regression (2) adds labour market controls for the percentage change in population between 2011 and 2015, to control for changes in the size of the labour market, and percentage change in employment over the same period to control. Given that votes were reported to have varied considerably, based on demographics, regression (3) adds controls for the percentage of a county's population that was Asian, Black, Female, Hispanic or Foreign born in 2015, all of which correlated negatively with support for Trump, per exit poll reporting at the time (Frey et al, 2018).

Regression (4) adds an education control, specifically the percentage of the population over the age of 25 who hold a bachelor's degree or equivalent in 2015. This again is significantly negatively correlated with support for Trump and had a notably large coefficient of some -47.07 beyond the 1% level. The inclusion of the education control also substantially reduces the effect size for the primary automation risk variable. This makes intuitive sense, as counties that have higher share of routine employment also typically exhibit lower educational attainment (Frey et al, 2018). Lastly, regression (5) factors out state-level differences, thereby only exploiting variation in changes in Republican vote share and automation risk within states.

Despite these controls, a positive, sizable, and highly significant correlation between support for Trump and routine work persists. These findings are further corroborated a similar series of regressions performed looking at the difference in support for Hilary Clinton in 2016 compared to Barack Obama in 2012 using an identical set of independent variables (see Table 5 in the appendix). These regressions find large and significant negative correlations between the percentage of a county's labour market composed of routine jobs and changes in support for Hilary Clinton.

Having used a similar methodology to Frey et al (ibid), it is unsurprising to find these results cohere with their existing analysis and lends further support to their hypothesis that exposure to automation risk played an important role in driving voters to support Trump in the 2016 general election. Having established this, we can now move on to the primary areas of interest of this paper: the 2020 candidacies of Donald Trump and Bernie Sanders.

TRUMP 2020

Table 2 uses an identical methodology to table 1 to analyse the factor's effecting Trump's electoral performance in 2020. All figures are updated to reflect the new time period, so the dependent variable is now the change in Republican vote share between 2020 and 2016, the independent variable of interest is the change in the percentage of the labour market comprised of routine jobs between 2019 and 2015, and control variables are labour market and demographic figures from 2019, as no ACS data has been published for 2020 at the time of writing.

TABLE 2.

	Outcome: Change of Trump's vote share General Election 2020 vs. 2016				
	(1)	(2)	(3)	(4)	(5)
Change in Automation Risk	0.12684***	0.12014***	0.09104***	0.04968***	0.02611**
Robust Standard Error	(0.01272)	(0.01294)	(0.01209)	(0.01567)	(0.01394)
Labour Market Controls?	No	Yes	Yes	Yes	Yes
Demographic Controls?	No	No	Yes	Yes	Yes
Education Controls?	No	No	No	Yes	Yes
State Fixed Effects?	No	No	No	No	Yes
R^2	0.0577	0.0634	0.1739	0.1806	0.3273
Number of Observations	3,107	3,107	3,107	3,107	3,107

*** p < 0.01, ** p < 0.05, * p < 0.1 All coefficients denote a percentage change in the popular vote.

Table 2 shows massive decrease in effect size across the board. Regression (1) shows the coefficient accounting for the percentage of the labour market comprised of routine jobs drop by some 99.6% compared to the 2016 election, with comparable decreases across each control regression. Furthermore, the R^2 value for regression (1) drops to approximately 40% the size it was in 2016, implying that automation risk was a far less decisive factor explaining the variance in Trump support in the latter election.

This suggests that the sizable decreases in effect size lends support to the theory that Trump, having become the status quo candidate, no longer meaningfully benefited from the votes of those whose jobs were at risk of being automated. This is further supported by another set of similar regressions looking at the difference in Democratic vote share between 2016 and 2020 as the dependent variable; they find a tiny, though highly significant, effect going in the other direction (see Table 4 in the appendix), suggesting that the average voter for whom automation was a priority found themselves essentially "politically homeless" in the 2020 presidential election. Those voters do not seem to have found the idea that either candidate was going to meaningfully address the issue credible, so they either voted along different lines or chose not to vote at all.

An argument could be made to interpret these results as suggestive that automation simply played a smaller part in the 2020 elections. While the economy was a top concern, it is not necessary that the issue of automation made up most of, or even a sizeable minority of voters' economics concerns. However, there are two reasons why this less plausible than the idea that voters simply did not believe Trump nor Biden would meaningfully address the issues they faced related to automation. First, the issue of automation was given a higher profile in the 2020 presidential campaign, notably in the democratic primaries by Andrew Yang, whose signature policy, the "Freedom Dividend," proposed a universal basic income of $1,000 a month to every American adult as a response to job displacement by automation (Yang, 2019). The issue also featured in Biden's policy platform (Thibodeau, 2020). Second, there is no apparent factor that would alleviate the concerns voters had related to automation in the 2016 election by the 2020 election. Technological progress continued apace; consciousness of the effects of machine learning (popularised as artificial intelligence) became more widely known (Agrawal et al, 2018) and while employment and economic growth rose for much of the Trump Presidency before the COVID-19 pandemic, there was no significant increases in average wages nor reduction in perceived worker precarity (ibid).

When taking this into account, the above results suggest that voters who had voted for Trump in 2016 because they believed that he would address their concerns about automation did not vote for him along the same lines the second time because they felt that he had failed to deliver on the issue, not because they suddenly stopped caring about the risk to their jobs.

SANDERS 2020

The regressions examining Bernie Sander's Primary campaign were constructed in an identical manner to those examining Trump's campaign in 2020, save for changing the dependent variable to account for the change in vote share experienced by Sanders between the 2016 and 2020 primaries on a county level.

TABLE 3

	Outcome: Change of Sanders' vote share Democratic Primary 2020 vs. 2016				
	(1)	(2)	(3)	(4)	(5)
Change in Automation Risk	0.17463***	0.20326***	0.21757***	0.13133***	-0.06478**
Robust Standard Error	(0.03744)	(0.03802)	(0.03207)	(0.0422)	(0.02597)
Labour Market Controls?	No	Yes	Yes	Yes	Yes
Demographic Controls?	No	No	Yes	Yes	Yes
Education Controls?	No	No	No	Yes	Yes
State Fixed Effects?	No	No	No	No	Yes
R^2	0.0076	0.0136	0.4318	0.4338	0.8251
Number of Observations	2,846	2,846	2,846	2,846	2,846

*** p < 0.01, ** p < 0.05, * p < 0.1 All coefficients denote a percentage change in the popular vote.

Interpreting the results of these regressions is more complex than the previous two groups; they are fundamentally less clear. At first glance, one could justifiably interpret these tables to suggest that there was no meaningful link between support for Bernie Sanders in 2020 and automation risk, much like the case of the Trump 2020 campaign. However, a closer examination of the results, particularly columns (1) to (4) suggests a degree of additional nuance may be warranted.

Column (1) sees the effect for Sanders being 38% bigger than the respective effect for Trump in the 2020 general election and column (4) sees the effect for Sanders being 167% larger than the corresponding effect for the same Trump campaign. Additionally, the size of the Sanders 2020 effect is close to the margin of victory in certain US states during the 2020 election (Arizona: 0.31%, Georgia: 0.24%, Wisconsin 0.63% (Leip, 2020) and a non-trivial component of the overall margin of victory (4.45%). While obviously this in no way alters the realities of the Sanders 2020 campaign's lack of success, it nonetheless is suggestive of a particular political priority of a definite set of voters large enough that a campaign manager or political advertisers might want to take notice.

This is especially true if one remembers that it is impossible to compare the Sanders 2020 campaign to the Trump 2020 campaign on a 1:1 basis: Sanders ran in the Democratic Primary, whereas Trump ran in the General Election. The nature of each contest is markedly different: US primaries feature multiple candidates and voting is staggered. Thus, the presence of tactical voting must be considered.

Unlike the general election, which presents a binary choice between two candidates, with voters picking who they prefer as president, in primaries voters not only might consider which of the candidates they prefer, but also who among the candidates is most likely win their preferred party the general election (Burden & Jones, 2006). Throughout the 2020 primary, media attention was given to the relative "electability" of Biden and Sanders (Otterbein, 2019) a consideration that may have induced some who agreed with Sanders' policy platform to vote for another candidate.

This seems to have been particularly true after the so called "Super-Tuesday" vote, the fifth of the eighteen sets of votes in the democratic primary. Two other democratic candidates dropped out of the race and declared their support for Biden, alongside a third candidate who had previously dropped (Korecki, 2020) leaving him with a decisive lead and all but guaranteed to secure the nomination. Polls showed that this depressed the turnout for Sanders; leading people to vote for Biden as they did not believe that Sanders had a chance of winning (Pew, 2020).

Despite these downward pressures, regressions (1) to (4) show a relationship between share of routine jobs and support for Sanders notably larger than the one experienced by Trump in the 2020 general election without these complicating factors. Put another way, these results give some indication that there was a meaningful relationship between support for Bernie Sanders, a candidate not of the extreme right who represented a credible break with the status quo, and voters with jobs that are at risk of being automated.

There are, however, complicating factors to this interpretation. The first and most obvious is the fact that when state level effects are controlled for, the coefficient of the automation risk variable becomes negative while staying statistically significant, as seen in regression (5). This could be explained away by pointing to the coefficient's reduced significance in both the Trump 2020 and Sanders 2020 regressions compared (1) to (4) (a significant at the 5% level compared to $P>|z| = 0.000$ for all other automation coefficients). Furthermore, one could argue that the inclusion of fixed effects might remove too much variation and overly downwardly bias the results, which, given its small starting size, could inaccurately reduce the effect.

Nevertheless, it is also possible that a link between support for Sanders and the share of the labour market composed of routine jobs is shown not to actually exist after factoring out traditional state-level divisions along party lines. Furthermore, the R^2 values for the Sanders 2020 regressions are notably smaller than those of either of the Trump campaigns. While the previous comments about the differences between primaries and general elections still apply, the fact that considerably less of the variation in Sanders' vote share can be explained by its correlation to automation gives weight to the idea that there is no meaningful relationship between support for Sanders and automation risk.

In short, these results are not conclusive. It would be good to perform similar analysis on a general election in a comparable country as the lack of complicating factors surrounding the primary process might make it easier to detect the effect of the appeal of non-far right anti-status quo candidates to voters at risk of automation, should such an effect exist at all.

6. Discussion

Several further comments should be made about the above results. First is the omission of a control variable for the percentage of jobs held in a county's labour market that are both routine and susceptible to being offshored. Frey et al (2018) include such a variable in their analysis of the 2016 election, as well as a variable accounting for the exposure of a county's workforce to Chinese imports between 1991 and 2011. The estimates of Frey et al's coefficients remained similar in size and significance after the addition of these controls which they took to reflect the considerable variation in automation within such economic sectors and a relatively limited overlap between exposure to automation and exposure to Chinese imports, offshoring and specialisation in routine work as show by Acemoglu and Restrepo (2017). While this likely leaves this paper's estimates of the factors affecting Trump's performance in 2016 in good shape, there is a non-trivial chance the same might not hold true for Trump in 2020 or indeed Sanders in 2020, given his frequent targeting of trade deals such as NAFTA and TIPP during his campaigns (Ebeling, 2015). Nonetheless, given the aforementioned limited overlap of the two kinds of labour market risk, it is assumed that the results for Sanders' and Trump's 2020 campaign would remain largely unchanged by the inclusion of such controls, though further analysis to test this assumption would be welcome.

A second comment is on the general robustness of these results. It is possible that the share of routine jobs in a given labour market may simply have been correlated with some unaccounted-for economic shocks that also affected the outcome of the election. Though a robust set of controls was used in the analysis they do not eliminate this possibility entirely. Frey et al control for this concern using two sets of instrumental variable analysis, the first looking at exogenous variation in the composition of the labour market by exploiting historical differences in its compositions. Concretely, they substituted the 2011 labour market composition with one from 1980 using US census data and use the difference between 1980 and 2015 as their variable of interest instead of the difference between 2011 and 2015.

The second strategy entailed exploiting different levels of exposure to automation across countries aside from the US. The authors construct an instrument that accounts for variation in exposure to automation across ten European countries, which is then cross referenced with geographic regions of the United States. Both instruments continue to find significant, sizable relationships between automation risk and the change in Republican vote share in the 2016 election.

However, again due to data constraints, performing such robustness checks was not possible. While there is a strong case to be made that this should have no effect on the robustness of the results of Trump 2016 analysis given its aforementioned similarities to Frey et al's results, the lack of robustness checks does raise questions about the validity of the analysis of the 2020 campaigns. This is particularly problematic as there was an exogenous economic shock that effected both the labour market composition and electoral outcome: COVID-19.

The best defence of the results is to point out that due to the fact that no ACS data has been published for 2020 at this time of writing, all controls were constituted of labour market and demographic data for the years prior to the election, 2019 (and 2015 for the 2016 election for the sake of consistency of the analysis). However, while there is no reason to think that COVID would have had any reason to effect American workers' exposure to automation risk in 2019, this in itself raises additional issues, namely given the massive disruption experienced in 2020, how representative 2019 labour market data is of the factors affecting voters in 2020. While voters are far from indifferent to the economic environment that prevailed during a politician's term in office, the magnitude of the pandemic may well have shifted voters' priorities. As well as massively accelerating socio-economic trends, such as working from home, the pandemic causing a considerable spike in unemployment, peaking at almost 15% in April 2020 (FRED, 2021). More troublingly, as the work of Jaimovich and Siu (2012) points out, the destruction of routine jobs tends not be a gradual phenomenon but happens in chunks during the aftermath of recessions. As such, it is probable that in 2020 many workers were let go from jobs that will be done by machines henceforth. According to above model, knowledge of this, or even the mere fact of this, many well have influenced how people vote. Unfortunately, it is impossible to investigate this now. Further analysis would be warranted when new ACS and census data is published to verify these results.

7. <u>Conclusion</u>

Before the Industrial Revolution, those in power had a habit of banning labour-saving devices for fear of the civil unrest they would cause (Acemoglu and Robinson, 2012; Mokyr, 1990). Looking forward, one estimate claims that 47 per cent of US employment is at 'high risk' of automation over the forthcoming decades (Frey and Osborne, 2017). As referenced at the beginning of this paper, new technologies like deep learning expose occupations that require advanced degrees to the risk of being replaced by machines; routine jobs are no longer the only ones that are threatened. The combination of these factors suggest that the politics of automation are only going to become more prevalent; understanding them will be increasingly crucial.

The findings of this paper suggest political leaders who fail to address voters' concerns stemming from automation once elected will quickly find themselves losing said voters' support, including insurgent politicians of the radical right. While this might be welcomed by those who fear the rise of such politics, this paper's findings are far less clear about what kind of political force voters will next turn to in order to address their concerns.

As the problems stemming from automation become increasingly complex, and politicians struggle to keep up with the rapid technological advances now seen, it seems dishearteningly probably that there will be considerable political chaos surrounding automation in the coming years. While no obvious solution presents itself to the turmoil it is worth remembering, that these advances do present the opportunity to fundamentally improve our lives. From instantaneously translating languages as we speak to each other, to hastening medical breakthroughs, the technologies behind automation hold vast promise. The question then, is not how do we stop automation, but instead how do we ensure all of society benefits, not just those whose jobs have been spared by the latest technological innovation. In a world which may well require fewer and fewer people's labour to maintain it, serious economic rethinking may be required to ensure the abundance derived from machines is widely and equitably shared.

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Appendix

A Note on the so-called Radical Left

Readers familiar with Im et al's 2019 paper may feel that I have overlooked their finding that there is a no significant connection between voters exposed to automation risk and support for the radical left. This is not a case. Im et al define those parties that have very left-wing economic agendas (in particular those with stated socialist or communist ideologies) as to belong to the radical left, whereas I define the radical left as those parties, individuals or views that are universally perceived as presenting a credible challenge to the status quo from the political left. Because I do not believe that the groups Im et al examine meet with this definition, I term them parties of the far-left instead. Therefore, the differences in my conclusions result from terminological discrepancies, rather than a difference in methodology or findings.

There are two reasons why I believe very left-wing parties cannot be grouped together as radical in Europe. First, since the Eurozone crisis, there have been a number of self-described leftist or left populist parties that formed parts of governments throughout Europe, who enjoyed electoral success on the promise of ending austerity but found that constraints imposed by international financial conditions and the European Council and Commissions rendered them unable to fulfil their promises (as was the case with SYRIZA in Greece in 2015).

Second, as Im et al note, most parties of the radical right are functionally very new, whereas their counterparts on the left have a longer history. One example of this would be that, the French communist party, which was founded in the 1920s and was the largest left-wing party in the country until the 1970s. Consequentially, many of these left wing parties have been involved in coalition governments during the period of secular automation, so will be considered by some voters to be partially responsible for it. As such, I posit many European voters would be sceptical of these parties' ability to deliver meaningful change to the status quo and reserve the term "radical" for only those parties that are perceived to be capable of bringing about change, whatever their political ideology.

BIDEN 2020

TABLE 4

	Outcome: Change in Republican vote share General Election 2020 (Biden) vs. 2016 (Clinton)				
	(1)	(2)	(3)	(4)	(5)
Change in Automation Risk	-0.24071***	-0.22477***	-0.1944***	-0.09232***	-0.04113***
Robust Standard Error	(0.01237)	(0.01268)	(0.01267)	(0.01595)	(0.01416)
Labour Market Controls?	No	Yes	Yes	Yes	Yes
Demographic Controls?	No	No	Yes	Yes	Yes
Education Controls?	No	No	No	Yes	Yes
State Fixed Effects?	No	No	No	No	Yes
R^2	0.0577	0.0634	0.1739	0.1806	0.3273
Number of Observations	3,107	3,107	3,107	3,107	3,107

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All coefficients denote a percentage change in the popular vote.

CLINTON 2016

TABLE 5

	Outcome: Change in Democratic vote share General Election 2016 (Clinton) vs. 2012 (Obama)				
	(1)	(2)	(3)	(4)	(5)
Change in Automation Risk	-24.24861***	-24.35059***	-19.80106***	-4.82217*	-7.49265***
Robust Standard Error	(1.53261)	(1.55049)	(1.58859)	(2.53787)	(2.63395)
Labour Market Controls?	No	Yes	Yes	Yes	Yes
Demographic Controls?	No	No	Yes	Yes	Yes
Education Controls?	No	No	No	Yes	Yes
State Fixed Effects?	No	No	No	No	Yes
R^2	0.0577	0.0634	0.1739	0.1806	0.3273
Number of Observations	3,107	3,107	3,107	3,107	3,107

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$ All coefficients denote a percentage change in the popular vote.