Engaged Robots, and Disengaged Workers: Automation and Political Apathy

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How does revolutionary technological change translate into the political arena? Over the last two decades, we have seen an important restructuring of employment relationships in post-industrial societies, and technological change is widely considered one of the main drivers of these transformations. This paper proposes a theoretical framework linking technological change with political apathy. Using hierarchical logistic modeling with varying intercepts by country and survey data from the European Social Survey from 2002 to 2018 for 23 European countries, I present evidence that individuals more exposed to technological change are less likely to feel close to a political party, participate in elections and take part in protests. Those individuals exposed to automation are about 10% less likely to be politically engaged than those respondents without exposure to automation risks. I also demonstrate that income levels and unionization rates substantially moderate the direct link between automation and political engagement. The impact of automation on political engagement is smaller among wealthier citizens and in highly unionized environment. The political message from these interaction effects speaks about the reinforcing forces between economic inequality and automation and the role of collective organization. My findings have important implications for understanding the links between structural change in labor markets and political inequality.

Introduction

In 2018, *The Guardian* posted a column titled "*Robots will take our jobs! We'd better plan now before it's too late*,"[1] and in 2020, the New York Times published an article entitled "*The Robots Are Coming. Prepare for Trouble*."[2] These titles have a provocative claim: technological change is here to compete for jobs and will cause the lost of many of them. Automation effects on the future of work have been lively discussed (e.g, Acemoglu and Restrepo 2020; Jaimovich and Henry E Siu 2019; Graetz and Michaels 2018; Dauth et al. 2018; Frey and Osborne 2017; Autor 2015). However, we know very little about how these structural labor market changes translate into politics. Recent studies show its effect on triggering anti-status quo and anti-establishment preferences (e.g., Frey, Berger, and Chen 2017; Bisbee et al. 2020; Owen 2020), but a question that has received relatively little attention is whether citizens are more or less likely to engage in politics when exposure to automation risks increases. Does the threat of automation reduce individual political engagement? Are workers at higher risk of replacement less likely to participate in elections? Do affected citizens speak up?

In this article, I argue that there are good reasons to expect that the threat of automation reduces individual's political engagement. First, automation may lead to individuals' perception of risk of losing their jobs, and job insecurity (Jaimovich and Henry E. Siu 2020; Erebak and Turgut 2021; Nam 2019; Brougham and Haar 2020; Anelli, Giuntella, and Stella 2021). Due to this economic uncertainty, individuals may fail to perceive themselves as meaningful political actors, diminishing their perception of political efficacy and increasing political alienation.

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[†]Appendix with replication codes and complementary analyses available via request by email mag384@pitt.edu.

[1]See February 1, 2018 (The Guardian)

[2]See new January 30, 2020 (The New York Times).

Second, the rise of automation has generated an unequal distribution of its consequences, therefore, connected to income inequality, which may harm political participation. To put it simply, in occupations where machines cannot execute tasks –"non-routine"– wages and employment have grown faster than in occupations where labor can be replaced by machines.[3] For instance, in the US, Acemoglu and Restrepo (2021) document the increase of wage inequality of the last four decades based on the changes in employment opportunities due to technological change. Thus, based on the power theory[4] I expect a decline in political engagement due to the current wave of automation.

Third, automation has caused a relative wage decline for workers that specialized in routine tasks in industries that experienced labor share declines (Acemoglu and Restrepo 2021; Jaimovich and Henry E. Siu 2020). This wage loss means that exposed workers will have fewer resources available, undermining their ability to mobilize.

There are, therefore, good reasons to expect that the threat of automation depresses political engagement. I investigate this hypothesis empirically by building on recently developed measures of individual-level risk of computerization (Goos, Manning, and Salomons 2014; Frey and Osborne 2017) based on occupation's characteristics (Autor 2013; Autor, Levy, and Murnane 2003). I test my hypothesis by examining 23 European countries from 2002 to 2018. I consider high-risk workers to be less likely to be politically engaged. Using the European Social Survey data, I measure political engagement by looking at attitudes, such as feeling close to a political party, and behaviors looking at turnout and participation in non-violent protest.

Overall my findings suggest that those citizens with higher-level exposure to automation are less likely to feel close to a political party (about 7 points less likely), participate in national elections (about 6 points less likely), and protest (about 2 points less likely). My analysis also demonstrates that automation effects are moderated by individuals' income levels, with the wealthiest individuals partially compensating for the harmful impact of automation on engagement. Social safety nets (proxied using unionization rate) also moderate automation effects, and I present empirical evidence for this relationship.

Finally, I analyze two individual-level mechanisms that could underlie the effects of automation exposure on political disengagement. I first consider individual frustrations regarding their economic situation, which may generate a feeling of loss that harms individuals' political engagement. Then, I evaluate sociotropic considerations, for instance, hopelessness regarding the future of work and society. I provide an illustrative mediation analysis of both channels, finding statistically significant support for them as mediators that trigger political disengagement.

These findings on how automation affects political engagement contribute to the broader literature about political participation and protest. This literature has typically focused on the effects of economic temporary shocks such as oil prices variation (Charles and Stephens Jr. 2013), unemployment in the business cycle (Burden and Wichowsky 2014), weather conditions (Horiuchi and Saito 2012), economic crises (Di Mauro 2016), among others. Automation, in contrast, is a long-term replacement shock. Those individuals who are affected will face a permanent income and status loss. Estimations for the US indicate that about 47% of the workforce is at risk of computerization (Frey and Osborne 2017). Recovering from such a shock will not be as easy as from temporary shocks such as declines in employment rates. Moreover, past studies have focused on other economic insecurity measures, such as income decline or inequality at the aggregate level, which may only account for partial evidence of this structural economic change.

[3]See Autor, Katz, and Kearney (2006), Goos and Manning (2007), Goos, Manning, and Salomons (2009), and Autor (2013, 2015)

[4]See for instance Solt (2015).

By focusing on individuals' tasks, we can estimate an objective measure of exposure to labor market risks due to technological change at the individual level

Viewing political engagement as a distinct political consequence has significant theoretical implications. If exposed workers were excluded from political representation, democracy could be at risk. A small but growing literature has analyzed the political consequences of technological change focusing on vote choices (Gallego et al. 2022; Gallego and Kurer 2022; Owen 2019; Anelli, Colantone, and Stanig 2021). These studies link automation risk with support for populist right parties. I contribute by suggesting we should also consider the impact on political disengagement and demobilization, that is, "exit" options from the political area. Thus, one complementary explanation for the increase of populism may be that some voters who previously supported mainstream parties are leaving the electoral arena due to political apathy, remaining only the radicalized citizens in the voting contest. Alternatively, political disengagement can be the path through which populist anti-politics rhetoric gain supporters among individuals vulnerable to robotization. Moreover, this study contributes by not just focusing on political attitudes; it analyzes behavior focusing on turnout and political protest.

Overall, these disruptive changes generate concerns about the future of work and the creation of political upheaval (e.g, Boix 2019; Frey, Berger, and Chen 2017; Helen V Milner 2021a). Institutions and liberal democratic values as we know them today may be under question, especially after the unexpected Covid-19 pandemic, which has accelerated the process of technological displacement (e.g., Coombs 2020).[5] These events emphasize the necessity for research on the political consequences of technological change.

Technological Change and Politics

Over the last two decades, we have seen an important restructuring of employment relationships in post-industrial societies. Technological change is the main driver of these transformations (Anelli, Colantone, and Stanig 2021; Helen V Milner 2021a, 2021b; Acemoglu and Restrepo 2021). Starting in mid 1990s a significant advance in robotic technology started, which scholars named the automation shock (e.g, Acemoglu and Restrepo 2020; Anelli, Colantone, and Stanig 2019). Figure 9 in the Appendix documents the abrupt rise in the stock of (industrial) robots in the United States and western Europe between 1993 and 2015. According to Acemoglu and Restrepo (2021) the task displacement due to robotization accounts for at least 50% of the changes in US wage structure. Moreover, estimations regarding the computerization of jobs, and its translation to employment for the US, for instance, suggest that 47% (Frey and Osborne 2017) of jobs are at high risk of automation.

The threat of automation has not seemed to go unnoticed by citizens. Millions of workers worldwide are beginning to fear that robots will replace their jobs. For instance, the special issue of the Eurobarometer in 2017 shows that three-quarters of Europeans consider that due to robot and artificial intelligence incorporation, jobs are at risk of disappearance (more jobs will be destroyed than new ones created). Moreover, about 72% of respondents agree that robots and artificial intelligence steal people's jobs, and 44% estimate that their current jobs will possibly be at least partially automated.

Automation, defined as the increase of tasks that can be developed by capital (Acemoglu and Restrepo 2018a) has two sides. One type of technological change implies displacement

[5]Many routine jobs have been displaced and may not be recovered soon nor ever. See, for example, New York Times news "How Tech Won the Pandemic and Now May Never Lose", July 2021.

effects, in which old tasks set by workers can now be automated (e.g., Acemoglu and Restrepo 2019, 2018a). Another type refers to the creation of new tasks that did not exist before, named reinstatement effects (e.g., Acemoglu and Restrepo 2019). Thus, automation generates a large group of losers and new winners. To put it plainly, the consequences of automation are routine- and capital-biased (e.g, Autor 2013; Acemoglu and Restrepo 2018b; Dauth et al. 2018; Graetz and Michaels 2018; Kurer and Gallego 2019). This phenomenon is known as job polarization, which means that in occupations where machines cannot execute tasks –non-routine– wages and employment have grown faster than in occupations where labor can be replaced by machines.[6]

Routine occupations mainly refer to middle-skill and middle-wage jobs prevalent in blue- and white-collar sectors (i.e., manufacturing, administration). For example, an accountant specializing in taxes now can be replaced by a tax filling software (e.g., Sprintax) or a truck driver by driverless vehicles. This affected group of workers represents a hollowing out of the middle class instead of just a decline of poor individuals (e.g., Kurer and Palier 2019; Jaimovich and Henry E Siu 2019). These labor market changes and their unequal consequences will likely have multiple political implications. For instance, it has been largely argued that the middle class is an agent of democratization (e.g., Lipset 1959; Moore 1966; Boix 2003; Acemoglu, Acemoglu, and Robinson 2006), thus, understanding the political consequences of the hollowing out of the middle matters for democracy.

Following, I propose some hypotheses and channels through which automation may translate into attitudes (higher political disengagement) and behaviors (lower political participation) of exposed individuals.

Automation and Political Attitudes: Political Engagement

Scholars aiming to unpack the causes and consequences of unequal levels of political engagement has grown in recent years (e.g, Bartels 2017; Gilens 2012). From a normative perspective, understanding the determinants of political engagement matters for political representation and, more precisely, for democracy. In this work, I contribute to this puzzle by incorporating automation risks as one of the determinants of political disengagement.

My paper contributes to three important strands of the participation literature. First, some scholars have documented the impact of economic grievances on psychological perceptions, such as changes in individuals' self-perception of efficacy and self-esteem. For instance, Marx and Nguyen (2016) analyze 26 European countries and show that unemployed individuals are less likely to perceive themselves as meaningful political actors. Along these lines, Beesley and Bastiaens (2020a) show that there is a lower sense of political efficacy among globalization losers. According to them, individuals exposed to globalization may display greater apathy, a lower sense of purpose in political participation, and lastly, more decline in their participation than those who feel they benefit from globalization. My work contributes to this discussion by focusing on a new dimension of economic distress, i.e., the re-structuring of the labor market after the incorporation of robotics and automation, which, rather than improving individuals' political engagement, may represent a source of anxiety and demotivation. Building on previous works, I further argue that the fear of being replaced by a machine may likely affect individuals' sense of political efficacy.

An additional dimension of technological change affecting political engagement is related to uncertainty. Structural economic disadvantage individuals due to automation are more susceptible to employment and wage loss, have fewer reemployment opportunities, and lower levels of job

[6]See Autor, Katz, and Kearney (2006), Goos and Manning (2007), Goos, Manning, and Salomons (2009), and Autor (2013, 2015)

security (e.g., Jaimovich and Henry E. Siu 2020; Patel et al. 2018). Along these lines, the recent work by Anelli, Giuntella, and Stella (2021) shows that the greater labor market uncertainty due to robotization re-shapes individuals' life decisions. In particular, they focus on marriage and marital fertility rates. My work focuses on a different outcome: political participation. I argue losers of technological change may become more concerned about "making ends" and become less engaged in politics. Along these lines, previous work has linked economic insecurities with political engagement. For instance, Solt (2008) shows that economically insecure individuals are less likely to discuss politics with friends and to be interested in politics.

The second strand of the political engagement literature upon which I build my work focuses on the effects of economic inequality on participation choices. Several works have documented the link between higher inequality and lower political participation (e.g, Solt 2010, 2015). Along these lines, the very recent work by Schafer et al. (2021) shows that income inequality and turnout inequality seem to reinforce each other. A similar conclusion has been raised by Kim, Kim, and Lee (2022) linking inequality, status mobility, and participation. Moreover, the recent work by Ritter and Solt (2019) shows that higher income inequality is negatively related to campaign contributions. I propose to study technological change, as it is known as one of the main drivers of labor market polarization and hollowing out the middle (i.e., rising inequality). Therefore, based on the relative power theory, I expect that higher inequality will be associated with lower political participation

My argument is that the unequal distributional consequences where the non-routine have more employment opportunities, and higher wages relative to the routine workers, may imply that the non-routine (winners) may be more powerful than the routine ones (losers). Therefore, non-routine may not just prevail in the political contest; they can also re-shape the political agenda and define the issues to be discussed (Solt 2015, 2010). This unbalances of power may jeopardize political responsiveness toward the losers and repeal their mobilization.

Moreover, looking at automation's effects on job polarization, I expect less participation since polarized societies are expected to engage less in soft protest. Dubrow, Slomczynski, and Tomescu-Dubrow (2008) argue that when elites have the power to control the distribution of resources, they will not be moved to protest, and neither will the disadvantaged group, which may feel apathetic.

Third, my paper speaks to the literature on resources and their link with participation. By re-structuring, the labor market, many jobs have been lost, and wages of those exposed to automation have declined. In this sense, my conceptual framework builds on the resource model by Brady, Verba, and Schlozman (1995), which assumes that income and time are critical for participation in politics. It has been established that routine workers have suffered a decline in wages and employment (e.g., Jaimovich and Henry E. Siu 2020; Michaels, Natraj, and Van Reenen 2013), which means that those workers may have fewer resources to mobilize; thus, I expect them to be less willing to participate. Moreover, from a micro perspective, I consider that since political participation and information are costly, as workers experience wage losses, the marginal benefits of being politically engaged will diminish.

In this work, I argue that the exposure to automation and its consequences on job stability and economic uncertainty have affected individual political engagement. I focus on three sides of it: attitudes toward parties (feel close), turnout, and participation in non-violent protest. By focusing on turnout, I engage with a large literature on the effects of temporary shocks on electoral participation. Some examples of these shocks are business cycles (Burden and Wichowsky 2014), levels of employment (Rosenstone 1982; Charles and Stephens Jr. 2013), weather conditions (Horiuchi and Saito 2012) income decline (Rosenstone 1982; Guiso et al. 2017; Schafer et al. 2021;

Shah and Wichowsky 2019; Solt 2008), economic crises (Di Mauro 2016). Most of these have shown that short-term economic adversity negatively affects turnout. More recently, scholars have analyzed the effects of long-term changes and political engagement, such as home loss (Shah and Wichowsky 2019), and globalization (Steiner 2010; Beesley and Bastiaens 2020b). My work lies closer to the latter group of scholars looking at the consequences of long-term changes, but I contribute by focusing on automation.

Regarding participation in political protest, although the conflict theory would argue they should increase with economic grievances (e.g., Asingo 2018; Grasso and Giugni 2016), resource theory and relative power theory tell us we should expect automation to depress protest (Solt 2015; Dubrow, Slomczynski, and Tomescu-Dubrow 2008). For instance Solt (2015) presents evidence linking less participation in nonviolent protests with high inequality. To make sense of these seemingly contradictory findings, I rely on Kurer et al. (2019) who argue that structural economic disadvantage (i.e., the level of grievances) unambiguously diminishes political protest. While the deterioration of economic conditions (i.e., a change in grievances) increases political activity. Based on the early work of economists, I expect that technological change has a long-term impact on the structure of employment, wages, and, more broadly, the organization of production (e.g., Acemoglu and Restrepo 2019, 2020; Graetz and Michaels 2018; Jaimovich and Henry E. Siu 2020). Thus, I argue that the level of grievances will dominate depressing political protests. Therefore, as powerfully demonstrated by early scholars, when citizens are at a disadvantage and governments seem unresponsive, they become politically alienated (Mair 2013; Schäfer and Streeck 2013; Offe 2019). Finally, the extensive use of technology in multiple tasks may make harder for "luddites" of the XXI century to emerge.

Following this understanding of individuals' exposure to automation and the consequences on political attitudes and behavior, my first hypothesis is as follows.

Hypothesis 1 ***Automation Disengagement****: The larger the exposure to technological change risks of an individual, the lower the probability of being politically engaged.*

The Moderating Effect of Income and Social Safety Nets

Turning to a final discussion about heterogeneous effects, I argue that automation's effects on political engagement are contingent on individual and societal context. In particular, I propose to discuss the role of income and social safety nets as moderators of robotization on political engagement. First, I argue that the importance of exposure to automation risk as a determinant of political engagement will be decreasing on current income. Again, relying on the resource theory, resources are necessary when engaging in politics, particularly in protest, which is a demanding activity. Thus, I expect that those individuals with higher incomes will be better able to afford the costs of being politically engaged (e.g., Brady, Verba, and Schlozman 1995). Along these lines, recent empirical works linking greater inequality with less political engagement have also shown that individuals below the top quintile do not seem affected their ability to participate in politics (Solt 2015, 2010; Ritter and Solt 2019). Among previous scholars looking at automation, only Thewissen and Rueda (2019) analyze together the role of automation risks and income for understanding support for redistribution.

My theoretical expectations imply that 1) income is associated with increasing political engagement; 2) automation risks are negatively associated with political engagement; 3) the interaction between income and automation risks is positive since I argue that income can compensate for the loss of political efficacy of losers of automation. To put it plainly, I expect that the effect of automation exposure will decrease as income increases. Thus, I posit the following hypothesis.

Hypothesis 2 ***Income***: *The effect of technological change on political engagement is lower for individuals with high income.*

Besides individual-level moderators of the relationship between automation and political engagement, I argue that contextual macro-level characteristics may affect the impact of automation. In particular, I propose that social safety nets, specifically unionization, moderate the link between individual exposure to technological change and political engagement. If an individual has relatively strong safety nets, then this risk of automation will become less decisive in determining her predisposition to participate in politics.

Unions have been largely argued to play a role in the process of mobilization of nonmembers, spreading political knowledge, and canvasing (e.g, Radcliff and Davis 2000; Lyon 2019; Iversen and Soskice 2015). All of these actions directly and indirectly contribute to promote turnout, and participation in non-violent demonstrations (Bucci 2017; Gest, Reny, and Mayer 2018; Zullo 2008; Ahlquist 2017). For instance, according to Lyon (2019) labor unions have an institutional role on democracy contributing to pro-poor political participation.

Unions can also help workers bargain for better job conditions, cushioning the insecurity generated by automation. As an illustration, I posit two cases. First, the United Auto Workers union, which bargained to have their assembly plant workers trained in robotics and technology to prevent job displacement (Khanna 2022). Second, US transport unions –especially truck divers– which are currently pushing legislators to regulate driverless vehicles.[7]

Thus, when surrounded by high levels of unionization, I expect that exposed individuals will be less likely to lose their sense of political efficacy and more likely to have resources to mobilize (i.e., shared resources due to the organization). This side of the argument contribute to the small but growing literature on the consequences of automation on unions and collective wage bargaining (Meyer and Biegert 2019; Balcazar and Castillo 2021; Haapanala, Marx, and Parolin 2022; Nissim and Simon 2021), but unlike them I focus on their interactive relationship.

To sum up, my theoretical expectation is that in a highly unionized environment, even structural labor market grievances due to automation will not be as strong to jeopardize political protest relative to an environment with unorganized collective action (positive interaction between unionization and automation risks). Thus, I present the hypothesis below.

Hypothesis 3 ***Union***: *The effect of technological change on political engagement is lower for individuals in highly unionized contexts.*

Research Design

In this section, I propose empirical tests for my hypotheses. I am interested in understanding how exposure to automation affects the probability of being politically engaged. I rely on the European Social Survey (ESS) to test my expectations. The ESS is a cross-sectional database of individuals who are nested by country. My sample contains ESS surveys between 2002 and 2018 (waves 1 to 9) for 23 Western countries[8] for which at least two waves are available. This database allows me

[7]See the recent hear in the US Congress January 27, 2022.

[8]Our sample includes Austria, Belgium, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Luxembourg, Netherlands, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, and United Kingdom.

to assess the individual perception of automation risks (key independent variable) and attitudes toward political apathy such as self-reported political engagement (dependent variable), as well as political behavior such as turnout and participation in non-violent protest (others dependent variables). It also includes critical variables for analyzing voters' behavior and preferences. Finally, I complement this database with country-level data from the Organization for Economic Co-Operation and Development database, and the Comparative Political Data Set (CPDS) by (Armingeon et al. 2017).

Measuring the Independent Variable: Exposure to Technological Change

My key independent variable is the exposure to technological change, which I approach using two different measures. First, I consider the influential measure developed by Frey and Osborne (2017) for the US case. They estimate occupations' probability of computerization using a Gaussian process classifier. Second, and again following the task approach, I use the routine task intensity (RTI) index developed by Goos, Manning, and Salomons (2014). They created this index from the Dictionary of Occupational Titles (DOT). In what follows, I explain with further details how these measures are operationalized.

These two measures are based on the task approach (Autor 2013), by which individual occupations and tasks have important consequences for workers' exposure to risks and economic well-being. This approach assumes that occupation characteristics are important determinants of which workers will be harmed (or benefited) by automation. Using both proxies, I estimate the models following the most accepted approaches to technological change. The advantage of considering all of them is that our results will be robust to multiple specifications and comparable to previous literature.

The probability of computarization proposed by Frey and Osborne (2017) has the advantage of using a novel methodology to categorize occupations depending on their susceptibility to being automated. It builds over the seminal work of Autor, Levy, and Murnane (2003), which I also use as my most straightforward measure, a dummy for the type of occupations with two groups. According to Frey and Osborne (2017) "computerization is now spreading to domains commonly defined as non-routine" (p.258); therefore, they claim a more dynamic measure is needed. For instance, tasks related to processing big data are associated with non-routine occupations, but nowadays, new algorithms are being developed, and new technologies can automate even these complex tasks. Their measure, therefore, has the uniqueness of providing estimation for what recent technological change is likely to mean for the future of employment.

The RTI index measures the log routine task input per occupation, subtracted the log manual and abstract task inputs (Goos, Manning, and Salomons 2014). It indicates that the more routine a task, the easier it is for a machine to execute it; thus, it is more likely to be replaced by a robot. The index goes from -1.52 –lowest exposure to automation– for managers of small enterprises to 2.24 for office clerks, highest exposure. I expect that citizens with higher risks associated with technological change will be less politically engaged.

The ESS provides detailed information about respondents' occupations. I use the variable that contains the International Standard Classification of Occupations (ISCO-08) to build my independent variable. The RTI index is defined using two-digit of the ISCO-88. Since the 6th wave of the ESS contains occupations using ISCO-08. I converted this occupation to the classification using ISCO-88. The harmonization comes from Thewissen and Rueda (2019). Then, the probability of computerization developed by Frey and Osborne (2017) uses the Standard

Occupational Classification (SOC) 2010. I built the latter one using a conversion from SOC to ISCO-88 following Thewissen and Rueda (2019).

Measuring the Dependent Variable: Political (Dis)Engagement

My empirical analysis uses three operationalizations of the dependent variable. First, to analyze the effects on political attitudes I look at individuals' closeness to a political party. Second, to approach political behavior I look at participation in national elections and protests.

Attitudes. The ESS provides us with a question that directly captures my main focus of interest: whether individuals are politically engaged. The question is the following: "*Is there a particular political party you feel closer to than all the other parties?*" This variable has two possible answers, yes or no. Therefore, my dependent variable is political engagement, a dummy that takes the value of one when a respondent states that she feels closer to a party; otherwise, it takes zero.[9] Similar questions have been used for previous studies looking to unpack political engagement, as well as partisanship effects (e.g., Mayer 2017; Reiljan 2020).

The assumption while using this question is that those individuals who identify with a party regardless of their party preferences are generally more likely to be involved in politics than nonidentifiers (Dalton 1984).

Political engagement in the sample has an overall mean of 0.46. To illustrate the differences in political engagement across occupations, Figure 8 in Appendix presents the proportion of politically engaged respondents by type of occupation. Each category of occupation corresponds to the RTI index developed by Goos, Manning, and Salomons (2014). The first bar of each quadrant represents the average by groups of routine and non-routine occupations. From the graph, we can see, on average, respondents from the routine group, the one more exposed to technological change, had a lower proportion of individuals who feel close to a political party. For instance, for 2012, the proportion of workers from routine occupations that were politically engaged ascends to 44%, while this proportion ascends to 55% among respondents from non-routine occupations.

Behavior. To understand political behavior changes, I propose using two operationalization of the dependent variable. My first dependent variable regarding political behavior is voter participation in elections (turnout). The variable was drawn from the ESS surveys, which include a question about whether the respondent voted in the last national elections. My second operationalization of political behavior is participation in nonviolent political protest such as public demonstrations. The ESS posits the question of whether the respondent had taken part in a lawful public demonstration during the last 12 months. Unlike closeness to a political party, the question used to approach political behavior refers to concrete actions rather than the willingness to protest or vote. This question has been previously used by scholars studying non-violent protest (e.g, Solt 2015)

Table 2 from the Appendix shows great variation across countries. Denmark is at the top of the list, with a high proportion of respondents saying they feel closer to a political party (75-69%). At the bottom, there is Poland, with the lowest proportion of individuals politically engaged (38-25%). The Table also summarizes the proportion of individuals who protest and vote by exposure to automation.

[9]It would be interesting to rely on a similar question regarding party leaders rather than parties. However, for data limitations, I will just focus on parties.

Operationalization of Control Variables

The literature on political behavior discusses several other factors that may affect individuals' political preferences and, in my particular case, the probability of political engagement. Following these scholars, I include in the model individual demographic controls for age, sex, years of education, a dummy for being a believer, union membership, and whether the respondent was unemployed (e.g. Frey, Berger, and Chen 2017; Gingrich 2019; Thewissen and Rueda 2019). Based on previous scholars, I expect older citizens, higher educated, and union members to be more likely to be politically engaged. In contrast, I expect unemployed respondents to be more politically disengaged.

I also control for variables at the country level. I incorporate into the model the unemployment rate. The data come from the OECD database. Based on the literature about economic hardship, I expect that a higher unemployment rate will lead to less political engagement (Frey, Berger, and Chen 2017; Thewissen and Rueda 2019). I also include social spending as a percentage of GDP, labor market protections, employment regulation restrictiveness, union coverage, industrial strikes. Unlike unemployment, I expect social spending, and labor market protections to positively correlate with political engagement (Gingrich 2019; Thewissen and Rueda 2019). I also incorporate economic and institutional control variables, such as openess which comes from the Comparative Political Data Set (CPDS), GDP growth, and foreign born rate. These variables allows me to incorporate some proxy to economic crises, and globalization. I expect them to be negatively related with political engagement. Moreover, I further incorporate alternative measures of risks such as offshoring and skill specificity (Blinder 2009; Owen and Johnston 2017; Iversen and Soskice 2001).

Table 1 in the Appendix summarizes descriptive statics for the main variables used in the analysis.

Analysis

The model

Individuals are nested within countries in my data, which means that the data's structure is hierarchical. To illustrate the variation across countries, Table 2 shows the average of political engagement by country and type of workers. To account for this structure –clusters of subjects within countries– I employ a hierarchical model that includes a random intercept by countries (multi-level model, MLM), which allows me to disentangle the influence of individual- and country-level characteristics. I start by analyzing the 6th wave[10] of the ESS, which corresponds to 2012, using a Bayesian hierarchical model to examine attitudes toward political engagement. Then, I study all the ESS waves pooled for all the dependent variables but using OLS hierarchical regression models with clustered robust standard errors.

My dependent variables, political engagement (in its three forms), are dummy variables, where one indicates respondents' self-report of political engagement. Since my dependent variables are dichotomous, I estimate logistic regression models. Thus, I assume the distribution of my dependent variable as binomial. My Bayesian hierarchical logistic model is as follows.

[10]Since running bayesian models is expensive (in terms of time) I used a sample including only one of the wave in the middle of the period.

$$
\begin{gathered}
y_i \sim \text{Binomial}(1, p_i) \\
log(p_i) = \beta X_i + \gamma Z_{j[i]} + \alpha_{j[i]} \\
\alpha_j \sim \text{Normal}(\bar{\alpha}, \sigma_\alpha) \\
\beta \sim \text{Normal}(0, 2.5) \\
\gamma \sim \text{Normal}(0, 2.5) \\
\bar{\alpha} \sim \text{Normal}(0, 2.5) \\
\sigma_\alpha \sim \text{Decov}(1, 1, 1, 1)
\end{gathered}
$$

where y_i refers to the likelihood and is related to the dependent variable, this distributes binomial since I assume that each individual i in my data can be thought of as having a Bernoulli distribution, with $Pr(y_i = 1) = p$; $Pr(y_i = 0) = 1 - p$, and this refers to the probability of being politically engaged or not. Then binomial is the generalization for the sample, which refers to multiple respondents being each of them Bernoulli distributions.

From that specification, X_i is a vector that contains individual-level predictors such as age or gender, the magnitudes of effects are captured with β coefficients. The impact of the country-level variables ($Z_{j[i]}$) is measured by the γ coefficients, with the subscript indexing respondents i within-country j, notation from Gelman and Hill (2006). Moreover, $\alpha_{j[i]}$ indicates the hierarchical random intercept. This parameter allows the model to vary the intercept across countries, and it is constant within a country.

I consider weakly informative priors, following *rstanarm*'s library default priors. These are not uniformly distributed (non-informative), but these priors are still not highly informative either (standard deviation of 2.5), so I consider them reasonable for my estimations. The fact that they are weakly informative helps me to regularize the estimation and stabilize the computation of "rstan." This means that a normal prior centered at zero, with a standard deviation of 2.5, and independent, was assigned for the vector of coefficients β, and γ. The prior was also assumed as a normal distribution regarding the varying intercepts. The parameters of this prior distribution, $\bar{\alpha}$ and σ_α, were also estimated using rstan default priors. That is for $\bar{\alpha}$ normal centered at 0, and scale 2.5. While for σ_α, it uses the family distribution called *decov*, in which each of the numbers specified represents regularization, concentration, shape, and scale, respectively. The Appendix "Computing and Convergence Diagnostic" contains the analysis of convergence for the model.

As suggested by the ESS, I employ survey weights to correct individuals' probabilities in the sample due to the sampling design used.

Results

Main Results - Automation and Political Attitudes

Figure 1 reports the estimates of logistic regressions, where the dependent variable is political engagement defined as closeness to a political party. I present two models per each of the approaches of the independent variable. The first one is my model without accounting for the structure of the data.[11] That is, without including random intercepts. The second model is the

[11] See the mathematical specification in the Appendix.

hierarchical model without including control variables.[12] In what follows, I present the analyses using as the primary independent variable the probability of computerization estimated by Frey and Osborne (2017). Since the estimation of the different models using the independent variable *RTI* and the dummy for routine occupation were consistent with the results following Frey and Osborne (2017) I keep them in the Appendix (see from Figures 23 to 36).

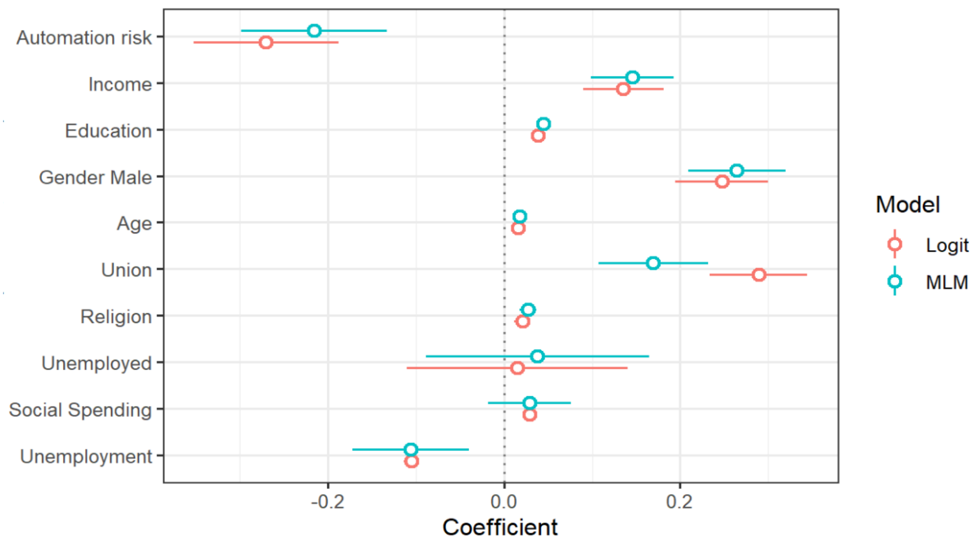

Figure 1: Results from the Bayesian logistic model without varying intercepts, and varying intercepts by country (MLM). Odd-ratios

Note: The dependent variable is political engagement operationalized as closeness to a political party, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

The plot shows the coefficients estimated –odds-ratios– and the Bayesian credible intervals to indicate when this interval includes the null hypothesis of no effect. Following Bayesian conventions, since the posterior distribution looks exactly as a normal distribution, then a symmetric interval around the posterior mean seems a reasonable assumption (e.g., CI at 1.96 standard error from the mean.). Figure 15 from the Appendix shows that the posterior for my key IV automation risk has a normal distribution.[13]

Figure 1 illustrates a negative correlation between automation exposure and political engagement. These results are consistent with my expectations. **Hypothesis 1** states that voters more vulnerable to automation risk would be less likely to be politically engaged, named as *automation disengagement*. This is the same to say that routine voters are associated with a higher probability of political disengagement; note that the estimated coefficients of the logit regression are negative, and their 95% credible intervals do not include the null hypothesis (zero effect). Still, looking at odd-ratios, we cannot interpret the magnitude of the impact, which I present in what follows. It is worth noticing that the estimation using a Bayesian logistic model and a Bayesian logistic MLM that allows the intercept to vary provides similar estimates for most of the coefficients.

[12]A third model varying intercept and slopes is presented in Appendix. Results remain unchanged.

[13]For the alternative specifications of the independent variable, RTI and routine, this assumption also hols since the posterior distributions also look as normal distrbutions (see Figures 22 and 31).

Only union membership is considerably different, and the automation risks variable has smaller odd-ratios when using MLM.

To better illustrate the results Figure 2 displays the predicted probability of political engagement (y-axis) as individuals have a higher likelihood of being automated (more exposed to automation risk), which is indicated on the x-axis. These marginal effects correspond to the second model without including control variables. The solid black lines represent the predicted point estimates per each group per which I allow intercept to vary, that is, per country. The shadow areas indicate the 95% credible intervals. The red line and shadow represent the global estimation for the model without control variables. Substantively, as the probability of automation rises from 0 to 1, there is a decrease of about 10 points on the probability of being politically engaged.

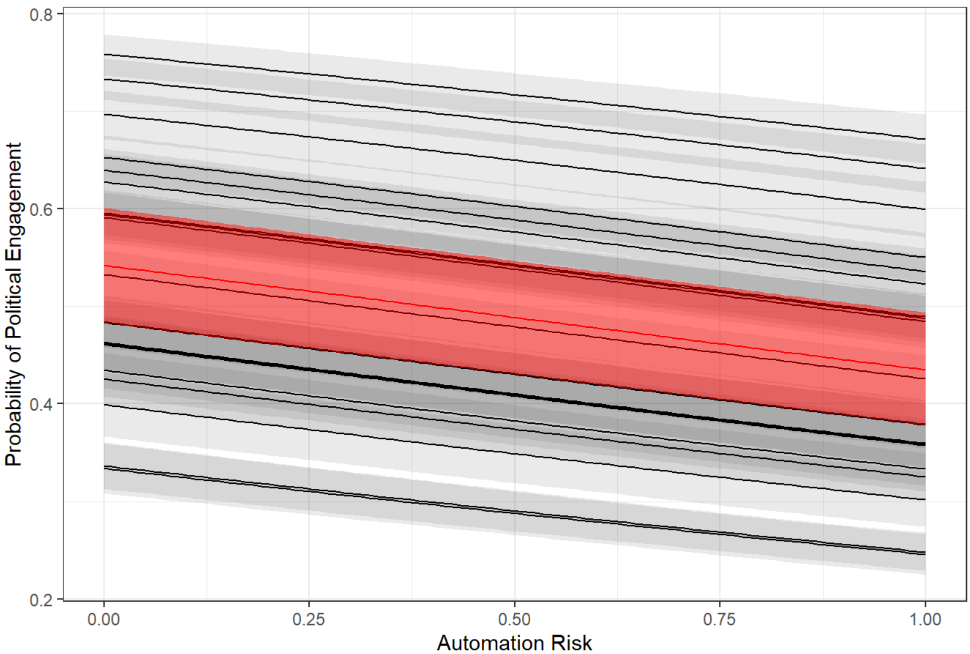

Figure 2: Predicted Probability of Political Engagement for Bayesian logistic model without additional explanatory variables
Note: The dependent variable is political engagement operationalized as closeness to a political party, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

This picture shows that as the exposure to automation increases, voters' probability of being politically engaged decreases significantly. For example, when the probability of computerization is at its minimum value (Frey and Osborne's measure equals 0.0038 in the sample), the probability of political engagement is the highest. This low exposure to automation corresponds to the "first-line supervisors of fire fighting and prevention workers" (p. 269). At the other extreme, when the probability of being replaced by a machine is almost one (Frey and Osborne's measure equals 0.99), the probability a respondent feels politically engaged is smaller relative to low-risk occupations. This extreme probability of being replaced by machines group includes new accounts clerks, tax preparers, and telemarketing.

The results are robust to various alternative specifications. For instance, the conclusions are similar when I estimate the marginal effects of the model, including control variables, leaving covariates at their observable values (see Figure 16 from the Appendix). Results remain significant and show a negative relationship between exposure to automation and the likelihood of being politically engaged. Again, from this figure, we can appreciate the importance of allowing varying intercepts since different countries start at a different level of the dependent variable. Note that as a robustness check, I estimated a model of varying intercepts and slopes, and even though we see a variation in the slope of the independent variable automation risks, it seems that most of the variation comes from the intercept instead of the slope (see Figure 18).

To help to illustrate the magnitude of the effect of technological change on political engagement, I estimate the average marginal effects of each variable, keeping the remaining variables at their observable values (see Figure 3). This approach is useful to interpret the contribution of my key independent variable in context. That is, relative to the contribution of other variables. Presenting the average marginal effects for the dummy variables is very straightforward since I calculate the predicted probability at the extremes, comparing when the variable takes the value of 1 and 0. This approach is the case for union membership, being unemployed, having a religion, and gender (male). The estimation is more challenging for continuous variables. For my key independent variable, since I am presenting Frey and Osborne's approach, I compare the extremes being around 0 and 1, representing almost no probability of automation and almost being sure that the task will be automated, respectively. Then, for the remaining continuous variables, I estimate the predicted probability of each variable at its quantile 25th and 75th.[14] This is the criterion used for the unemployment rate, social spending, income, education, and age.

Figure 3 reveals a non-irrelevant effect of the risks associated with technological change and the probability that an individual is politically engaged. First, comparing my variable of interest with the dichotomous control variable, we can see very precisely that *automation risk* is the largest average marginal effect in absolute terms. That is, the average marginal effect is above 0.07. The closest in terms of magnitude among the dichotomous variable is gender, then union membership precisely at 0.05, followed by religiosity, which is very close to 0, and finally unemployed, which credible interval contains 0. Moreover, automation risk is the only one that is negatively associated with political engagement among all these variables.

Then I compare my key independent variable, automation risks, with the continuous control variables. The variable with the most considerable contribution is *unemployment* rate. The interpretation for it is that a country with high unemployment ascends to 12.3% while one with low unemployment rates to 6.3%, with all else equal, then the average marginal effect is close to 0.15. In other words, the probability of being politically engaged in a country with a high unemployment rate drops considerably compared with a country with very low unemployment. This result is consistent with previous literature (Rosenstone 1982). Note that the average marginal effect of automation risk is smaller than unemployment rates.

Age also has an important effect on political engagement. As I expected, older individuals are more likely to be politically engaged, which may be explained by a higher level of political knowledge. An individual who is 63 years old will be more prone to be politically engaged, all else equal, than a respondent who is 34 years old. Again this effect is more prominent than technological change.

Interestingly, *automation risk* has a more considerable contribution rather than years of education. The average marginal effect between a high-skill respondent (15 years of education)

[14]Note that the results and interpretations remain almost unchanged when I consider as extremes the 10th and 90th quantile. See Figure 17 in Appendix.

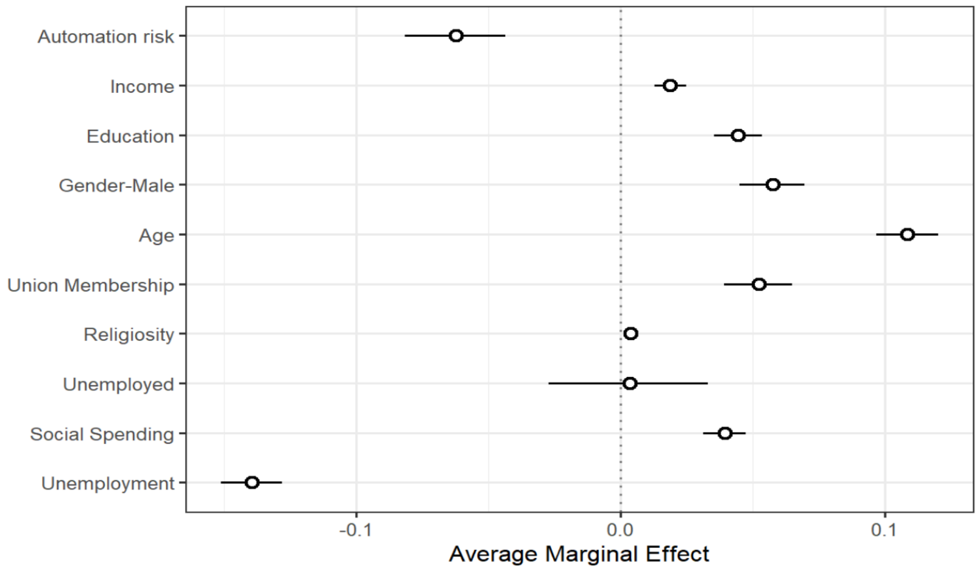

Figure 3: Average marginal effects (AME) for Bayesian logistic hierarchical model varying intercept by countries with additional explanatory variables.
Note: The dependent variable is political engagement operationalized as closeness to a political party, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS. AME estimated with other variables at their observable values.

and a low-skill respondent (10 years) is close to the impact of automation risks but smaller than 0.05. The same can be said regarding social spending, all else equal, after comparing countries with a high and low social spending rate over GDP. Finally, regarding income, automation seems to contribute three times more than income to explain the respondents' political engagement probability.

By comparing the effect of the probability of automation with those other explanatory variables, I aim to put the contribution of technological change in context. This comparison is important since one of the most influential theories has focused on the role of skills –education (Iversen and Soskice 2001). Therefore, my results of the critical role of technological change contribute to the comparative political economy literature by showing that level of education may not be explaining all the changes in political preferences. This finding goes in line with the theory proposed by Thewissen and Rueda (2019) who find risks associated with technological change more substantive in determining redistribution preferences than skills.

The results are robust to various alternative specifications of the independent variable. I have estimated the models using the independent variable as the *RTI* index and a dummy for *routine* occupation of the respondents. We can see a negative relationship between exposure to automation and political engagement for all the cases. This negative association remain no matter the operationalization of the independent variable, the inclusion of additional variables, or allowing the intercept or slope to vary.[15]. This means that there is strong support in favor of the hypothesis of this work, which claimed that more exposed individuals are the ones less likely to be politically engaged.

[15]See for example Figures 27, and 33 that present the average marginal effect for the models using the RTI index and the routine dummy as IV respectively.

To further test the robustness of the associations between automation risks and political engagement, I model automation risks with varying intercepts by country and allow random effects in the slopes of the probability of automation. I employ stan's default priors for all the parameters.[16] [17] The substantive reason for allowing this variation is that the probability of a task being automated may evolve differently by country depending on the types of investment in technology. For example, it may be the case that a country such as Germany[18] with the highest rate of robots incorporation can have a sharper relationship between automation risks and political engagement. In contrast, in a country where the incorporation of technology happens at a lower rate, the divergence among respondents' political preferences may vary less. The associated relationship between automation risks and political engagement remains negative, and the credible interval relative to the odds ratio does not include 0 (see Figure 19).

A final test of robustness is to estimate the models for all the waves of the ESS. In this case, I implement the OLS hierarchical model, and again, the results are similar. Tables 3 and 6 present these results.

Overall, the results of my empirical analysis regarding political attitudes provide robust evidence supporting my argument of the existence of an *automation disengagement* effect. That is, more exposure to automation is negatively correlated with political engagement, or what is the same positively correlated with *political disengagement*. As the probability of automation rises from 0 to 1, there is a decrease of about 10 points on the probability of being politically engaged in the model without controls (Figure 2), and about 5 points when accounting for additional explanations (Figure 3). In other words, less exposed to automation risk respondents are about 10% more likely to be politically engaged than highly exposed ones. Moreover, several of the control variables also contribute to explaining political engagement. Men, union members, and believer respondents are more likely to be politically engaged at the individual level. Older, richer, and more educated individuals are also more likely to feel closer to any political party. At the country level variables, a greater rate of social spending over GDP is positively correlated with political engagement, while the unemployment rate is negatively associated.

Main Results - Political Behavior

Figure 4 presents the results regarding technological change and political behavior (i.e, turnout and participation in non-violent protest). **Hypothesis 1** states that those individuals more exposed to technological change risks will be less likely to participate in elections and to take part in political protest. The Figure below presents the estimated effects of automation on turnout (blue) and participation in protest (red). The Figure 4 shows that the estimated effect for both proxies is negative and statistically significant different from zero, which allows us to reject the null hypothesis of no relationship between automation and participation. The magnitude of these effects are similar to the one presented earlier regarding closeness to a political party, so I will not further discuss it. Tables 3 to 8 in Appendix present different model specifications, and the models with further details.

To further illustrate how automation affects political behavior –turnout and participation in protest– I estimate the average marginal effects of each variable, keeping the remaining variables at their means (see Table 9). We learn from these results that automation risks play an essential role

[16]See appendix for the specification of the model with default priors.

[17]See appendix "Model Comparison" for a discussion about the information criterion WAIC about each one of the estimated Bayesian models.

[18]Germany has almost quadrupled the number of robots installed per worker in the last two decades (Dauth et al. 2018).

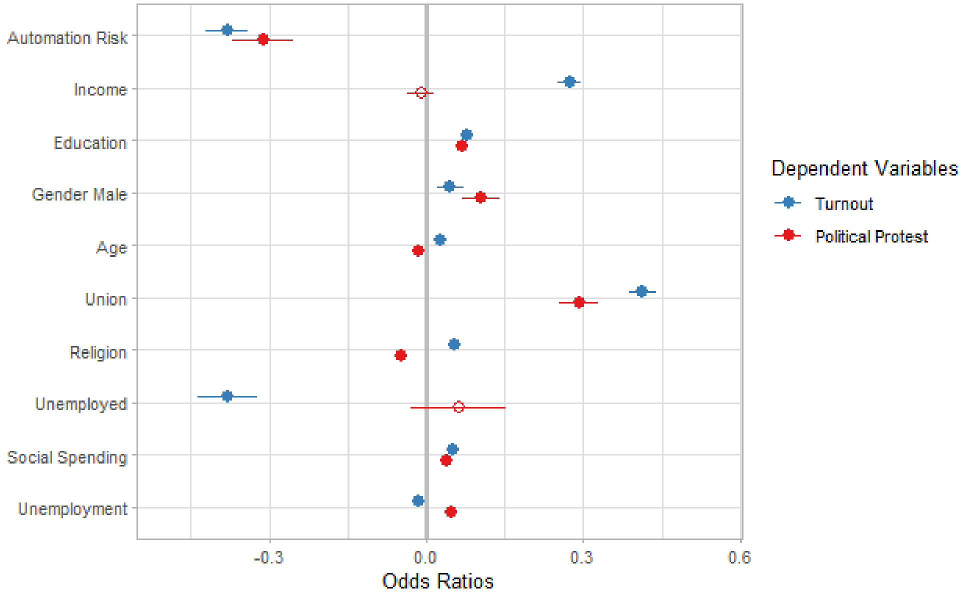

Figure 4: Results about political behavior from the logistic model. Odd-ratios
Note: The dependent variable are turnout and political protest, and the independent variable of these models is exposure to automation approached following Frey and Osborne (2017). Data comes from 1-9 wave of the ESS.

in explaining these variables. More precisely, the table shows that the magnitude of automation is among the largest. For turnout, if we compare an individual with low risk with one with high risk, the latter one will have a probability of participating in elections 5.6 points lower. We see unemployed with similar effects on turnout (decline of 8.3 in probability). Then, affecting positively, we see age and education increasing 24.4, and 9.9 points the probability respectively. Regarding protest, automation risk declines 1.7 points the likelihood of joining a non-violent demonstration.

These results are robust to multiple specifications of the models. Table 10 presents robustness checks including country and year fixed effects. Then, Table 11 includes as control variables offshorability of the task (Walter 2017; Blinder 2009), and skill specificity (Iversen and Soskice 2001). Results remain negative and statistically significant for each of the operationalization of the dependent variable supporting in all the cases the negative associations between automation and political engagement (attitudes and behaviors).

Overall, I find considerable evidence to support **Hypothesis 1** about the harmful effects of automation on political engagement in its three operationalization: closeness to a political party, turnout, and protest. Those individuals more exposed to technological change risks are less likely to be politically engaged on average. More specifically, individuals with low risk relative to high risk represents a decline of 7.4 points in terms of political engagement attitudes, 5.6 lower probability of turnout, and 1.7 points lower chance of joining a protest.

Evidence for the Moderating Effect of Income and Social Safety Nets

Thus far, my analysis has focused on the negative effects of exposure to automation risks on political engagement. I now aim to test whether this relation is moderated by income and social safety nets. **Hypothesis 2**, following the resource theory, posits that income would compensate the effects of technological change. Richest individuals will have more resources to engage in politics (e.g, make campaign donations) even though they may be at risk of automation. As I have argued earlier, I expect technological change will still negatively affect political engagement, but the impact will be stronger among citizens with low resources.

Moving forward, I now inquire whether the relationship is moderated by social safety nets, which I proxied as unionization rate. **Hypothesis 3** posits that in those contexts with a high level of unionization, the adverse effects of technological change should be compensated (fully or partially).

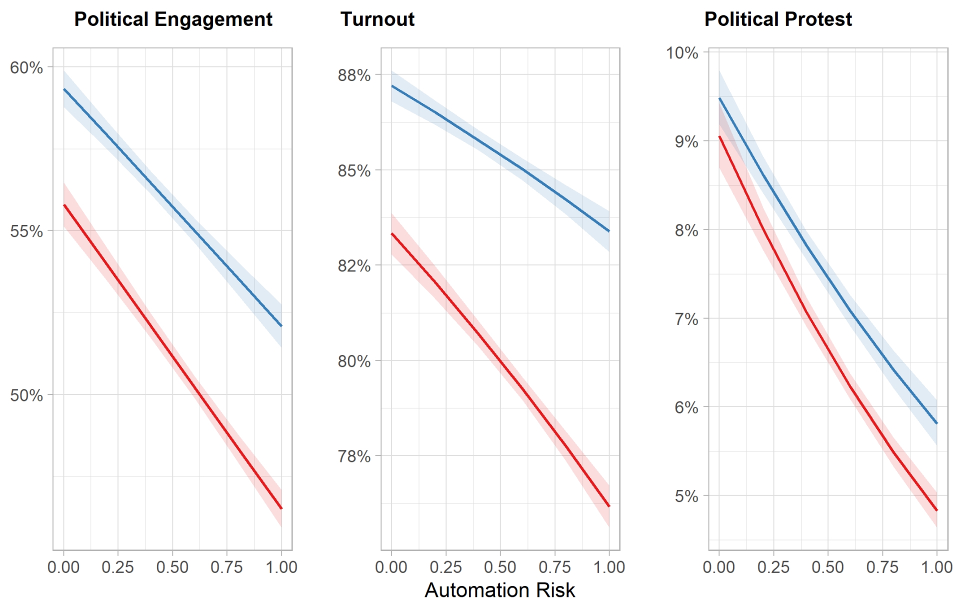

Figure 5: Moderation effect of income: poorest quintile (red) vs richest quintile (blue)
Note: Solid lines represent predicted probabilities and shaded regions represent the 95 percent confidence intervals of these predictions. The predicted probabilities were generated by fixing all other variables at their mean values. The independent variable of these models is exposure to automation approached following Frey and Osborne (2017). Data comes from 1-9 wave of the ESS.

The results regarding **Hypotheses 2-3** for the three operationalization of political engagement are presented in Figure 5 and 6.[19] Figure 5 shows that automation risks sharply reduce political engagement in all three proxies: closeness to political parties, turnout, and protest. To further illustrate the moderation effects of income, consider the turnout plot (middle figure). It shows that a typical non-routine individual from the richest quintile (blue line) was estimated to have around 88 percent chance of participating in national elections. This probability drops about 5 percent for a typical routine and rich individual. For the poorest quintile, the predicted turnout

[19]To obtain these results I add the discussed moderators into the models presented for Hypothesis 1.

probability is around 83 for a non-routine individual, and it falls to 77 percent chance when routine. The center panel shows that the turnout gap between the richest and poorest citizens increased as automation risks go up, which tells us that income does compensate for the negative effects among the richest individuals. Similar comments apply to the others proxies of political engagement. Table 12 in Appendix contains the estimated coefficients for each variable and the interaction between income and technological change.

Figure 6 shows that automation risks sharply reduce political engagement, as well as the heterogeneous effects of social safety nets in all three proxies: closeness to political parties, turnout, and protest. Again, to further illustrate the moderation effects of unionization, we can consider the turnout plot (middle figure). It shows that a typical non-routine individual in high unionized contexts (blue line) was estimated to have a near 91 percent chance of participating in national elections. This probability drops about 4 percent for a typical routine in a high politically mobilized environment. For the lowest unionized quintile, the predicted turnout probability is around 81 for a non-routine individual, and it falls to 75 percent chance when routine. Similar comments apply to the political engagement proxied as closeness to political parties.

Interestingly, the third plot containing political protest shows that participation in political protests is, on average lower in highly unionized environments. Still, we see that unionization partially compensates for the harmful effects of automation in political engagement (i.e., blue lines are always flatter than red ones). See Table 12 for further details.

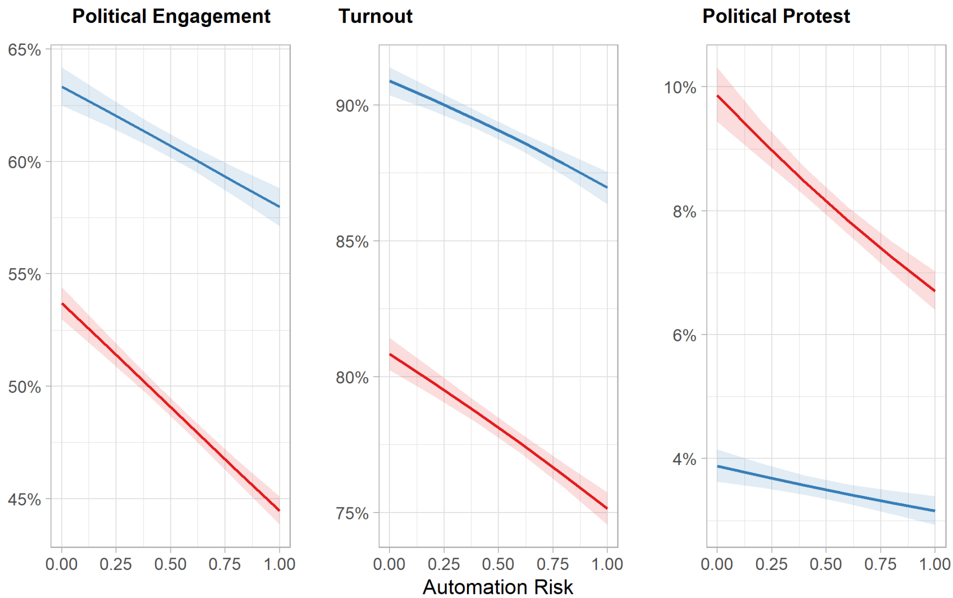

Figure 6: Moderation effect of Social Safety Nets: lowest unionization quantile (red) vs highest unionization quintile (blue)
Note: Solid lines represent predicted probabilities and shaded regions represent the 95 percent confidence intervals of these predictions. The predicted probabilities were generated by fixing all other variables at their mean values. The independent variable of these models is exposure to automation approached following Frey and Osborne (2017). Data comes from 1-9 wave of the ESS.

Mechanisms: Egocentric and Sociotropic attitudes

The above analysis demonstrates that structural economic changes due to technological change depress political engagement (i.e., closeness to political parties, electoral participation, and political protest), but what are the causal mechanisms underlying these findings? I suggest two mechanisms explaining why those individuals more exposed are politically disengaged. First, I posit that individuals behave politically disengaged because they negatively evaluate their own economic situation. In other words, based on egocentric considerations (i.e., pocketbook motivations). Thus, as they are personally exposed to technological risk, they will have a lower propensity to participate in politics. This argument aligns closely with the recent empirical evidence linking the decision to abstain with egocentric assessments (Habersack et al. 2021; Braun and Tausendpfund 2020).

Second, I argue that another channel through which automation may translate into political disengagement is through sociotropic considerations. In particular, the evaluation of objective national economic conditions. By allowing this second mechanism, I admit that individuals may have a lower propensity to be politically engaged as they perceive some economic constraints may threaten their country. That is to say, a sense of shared deprivation and feeling of hopelessness regarding societal economic welfare may also reinforce political alienation. Along these lines, a growing consensus about the impact of globalization is that it is channeled more by sociotropic evaluations rather than egocentric ones (Mansfield, Milner, and Rudra 2021; Mansfield and Mutz 2009).

To shed light on whether the suggested causal mechanisms can truly explain why technological change generates political disengagement, I conduct an illustrative mediation analysis[20] by linking automation through political engagement via egocentric and sociotropic considerations. Specifically, I employ two questions from the ESS. Egocentric considerations are proxied as agreeing with a statement about respondents' satisfaction with their own economic status. The answers range from 1 (dissatisfied) to 4 (satisfied). Then, sociotropic evaluations are measured with respondents' satisfaction with the present state of the economy in their country. This is an 11-point scale ranging from 0 (dissatisfied) to 10 (satisfied). Previous works have proxied egocentric and sociotropic evaluations in similar ways (e.g, Hays, Lim, and Spoon 2019; Braun and Tausendpfund 2020).

This analysis shows that automation is associated with a lower level of satisfaction of individuals' assessment of their personal socioeconomic conditions and satisfaction with national economic conditions. Lastly, these work as channels through which the effect of automation exposure translates into political disengagement. Figure 7 presents suggestive evidence in this direction.[21] In particular, the coefficients related to both of these mechanisms are negative and statistically significant for each one of the dependent variables. Substantively, these results suggest that economic insecurities due to automation may trigger egocentric and sociotropic individuals' attitudes which triggers them into political apathy.

[20]Following the guidelines proposed by Imai et al. (2011) and Keele, Tingley, and Yamamoto (2015).
[21]Tables 13, and 14 contain detailed results from 1st and 2nd stage of the mediation analysis.

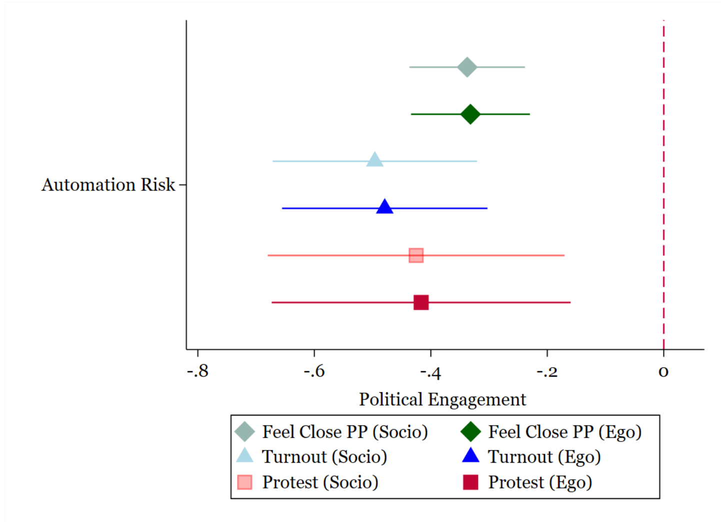

Figure 7: Mediated effects of automation on political engagement.
Note: Coefficients of 2nd stage of mediation analysis, showing the impact of the probability of computerization on two potential channels linking automation and political engagement: egocentric (measured with an item regarding satisfaction with personal economic situation, dark colored), and sociotropic evaluations (measured as satisfaction with national economy, light colored). The plot shows the estimation for each one of the dependent variables: political engagement, turnout, and political protest. The bars represent 95% CIs. The model contains individual and regional-level control variables. Fixed effects at the regional level are included; SEs are clustered at the region level.

Conclusion

How do structural economic changes such as automation translate into individuals' political engagement? Building upon previous research, this article has provided a theoretical framework and evidence to understand how structural economic changes can shape individuals' political attitudes and behavior. I have argued that the risks associated with technological change are significant to understanding voters' political apathy. I have also offered mechanisms for linking the automation revolution and divergence in political engagement. I have argued that because technological change generates a decline in wages and the share of employment and more economic insecurity among workers from occupations likely to be automated, workers will be less politically engaged.

Through a cross-sectional empirical analysis covering voters' political preferences in 23 European countries from 2002 to 2018, I have demonstrated that losers of automation –those who work in routine occupations easily replaceable by machines– are more likely to be politically disengaged. I test this effect with a Bayesian hierarchical framework that allows varying intercepts by country and adopts weakly informative priors (using rstanarm library in R) for 2012 and OLS hierarchical models for the complete sample.

My findings have important implications for the comparative political economy literature. I have shown that exposure to automation risks is very influential for understanding political attitudes, such as closeness to political parties. Even more interesting, the magnitude of the effects is as important as education or the level of income of individuals. Automation risk is associated with a significant and negative impact on an individual's probability of feeling closer to any political party. Those less exposed to automation risks are about 10% more engaged than the losers of automation. I show that these results are robust to multiple measures of my key independent variable and model specifications. This study also provides evidence for changes in political behavior. I have shown that those more exposed to automation risks are 5.6 points less likely to participate in national elections (turnout) and 1.7 points less chance to participate in public demonstrations (political protest). To sum up, these results show that automation risks affect political attitudes and political behavior, depressing political engagement.

I have also presented evidence that the effects of automation risks are moderated by individuals' income levels and social safety nets. Wealthier individuals are more politically engaged since they have more resources, and the evidence points toward some degree of compensation for the negative effect of technological change. The findings also offer an interesting picture when incorporating the role of social safety nets such as unions, compensating for automation's adverse impact on political engagement. These heterogeneous effects have substantively relevant implications. In addition to the increase in job polarization due to automation, those individuals with high income will be less affected in terms of their political engagement; therefore, income inequalities and job polarization may reinforce each other causing unequal representation. Moreover, the lack of strong unions representing workers' interests may increase the negative impact of automation on political engagement.

This study has also offered preliminary evidence about the channels through which technological change may affect political engagement. I empirically tested the interplay of technological change with egocentric and sociotropic considerations of the economy. Automation risks seem to trigger pocketbook and sociotropic concerns, which translate into political alienation (i.e., less political engagement and participation).

There are also significant political implications that emerge from these findings. First, if losers of automation are politically disengaged, they may be more prone to persuasion by anti-establishment or anti-politics rhetoric. Hence, they may become the reservoir of far-right populist candidates. This may help us understand the rise of populist support among those vulnerable individuals. Second, disengaged citizens may choose to stay out of elections. If the most affected by technological change are not part of the political arena, the unequal representation may worsen and undermine their ability to influence politics. Both of these alternatives could put the foundations of democratic systems at risks.

Given the concerns about the future of democracy due to automation, as expressed by Boix (2019), Helen V Milner (2021a), and endorsed by this paper's findings, developing redistributive income policies and strengthening unions could be a natural response to the effects of robotics on the decision to participate in politics. Future research exploiting longitudinal data or experimental design may shed further light on the mechanisms. Moreover, future research should formally test the link between political disengagement and far-right populist support. Also, to better evaluate the impact of automation on political representation, future work should analyze whether winners of technological change are gaining political influence.

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Appendix

Summary Descriptive

TABLE 1: Descriptive statistic: Micro-level data from ESS 2002-2018 and contextual variables from OECD and CPDS databases.

	Mean	Median	S.D.	Min.	Max	Obs.
Closeness to a Political Party	0.49	0.00	0.50	0	1	331014
Participation Protest	0.07	0.00	0.25	0	1	336880
Turnout	0.78	1.00	0.41	0	1	307848
Automation Risk	0.55	0.64	0.33	0	1	257539
Years of education	12.57	12.00	4.18	0	25	337949
Male	0.48	0.00	0.50	0	1	337816
Age	47.17	47.00	18.44	13	99	337949
Union membership	0.40	0.00	0.49	0	1	334426
Religious	4.58	5.00	3.03	0	10	335368
Unemployed	0.04	0.00	0.19	0	1	337949
Income	1.00	0.85	0.72	0	48	251775
Lag social spending	22.38	22.23	4.43	13	32	337949
Openess	102.98	86.95	44.76	48	281	307107
GDP growth	2.22	2.20	2.27	-5	10	337949
Foreign Born Rate	9.23	7.84	7.85	0	74	223673
LMP	1.81	1.73	0.97	0	4	283544
Unemployment rate	7.96	7.41	3.95	2	25	337949
EPL	2.35	2.33	0.68	1	5	227946
Union coverage	65.32	70.00	25.40	15	100	235316
Industrial strikes	266.19	17.00	1148.56	0	12765	204963

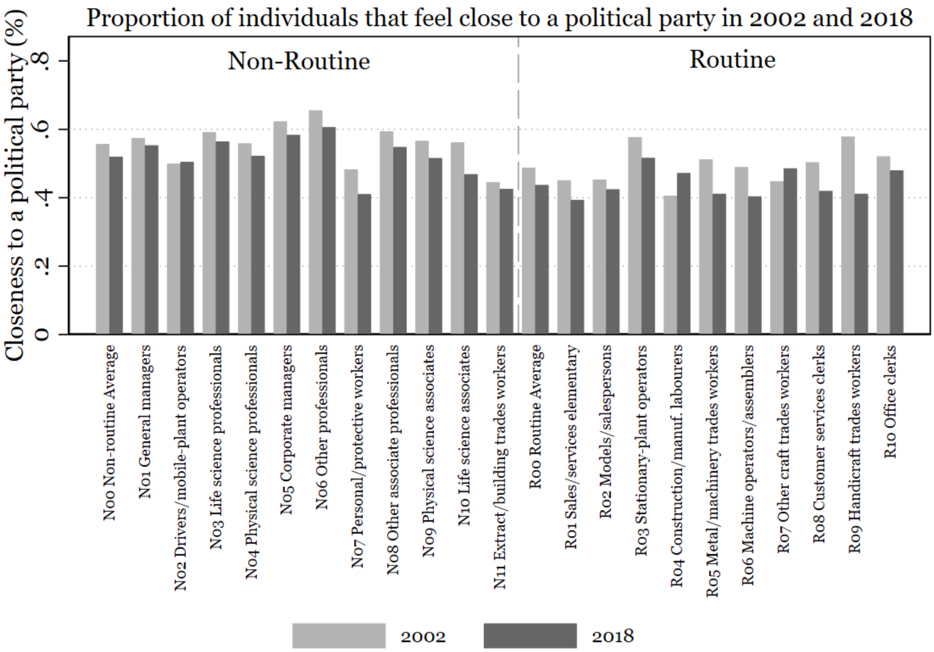


Figure 8: Closeness to a political party 2002 and 2018
Note: Source: Author's own calculation, using the ESS (2002-2018)

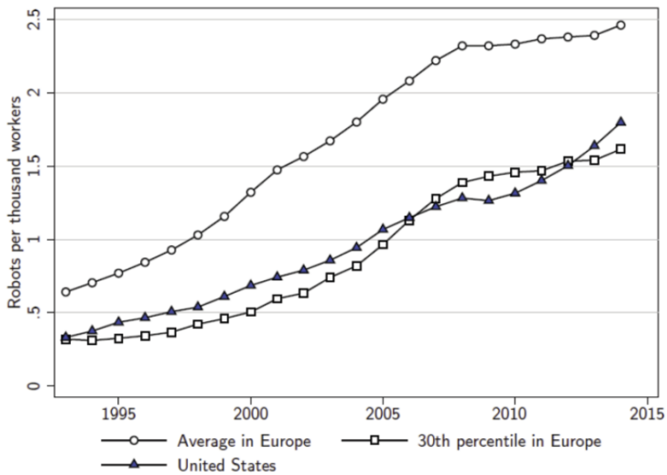
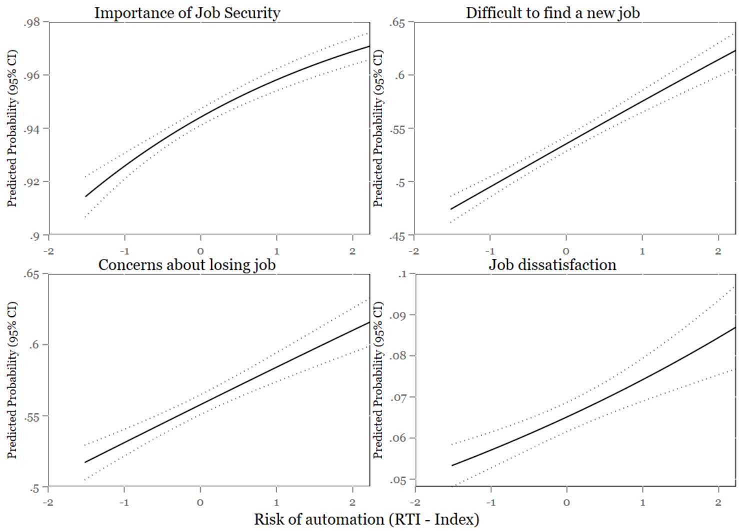


Figure 9: Industrial robots in the United States and Europe
Note: Industrial robots per thousands workers in the United States and Europe. Data from the International Federation of Robotics (IFR) Source: Acemoglu and Restrepo (2020)

Figure 10: Importance of job security, Difficulties to find a new job, Concerns about losing the job and Job dissatisfaction



Source: Author's own calculation based on ISSP data (1997, 2005 and 2015)

TABLE 2: Proportion of respondents politically engaged by country, and routineness (dummy)

	Political Engagement			*Turnout*			*Protest*		
Country	**Non-Routine**	**Routine**	**Difference**	**Non-Routine**	**Routine**	**Difference**	**Non-Routine**	**Routine**	**Difference**
Austria	0.60	0.49	0.11	0.91	0.82	0.09	0.09	0.05	0.05
Belgium	0.60	0.47	0.13	0.93	0.89	0.04	0.08	0.06	0.02
Czech Republic	0.47	0.36	0.10	0.73	0.57	0.16	0.07	0.05	0.02
Denmark	0.75	0.69	0.06	0.97	0.90	0.07	0.07	0.07	0.01
Estonia	0.50	0.39	0.11	0.81	0.60	0.21	0.03	0.02	0.01
Finland	0.62	0.52	0.09	0.90	0.78	0.12	0.03	0.02	0.01
France	0.60	0.46	0.13	0.80	0.70	0.10	0.18	0.12	0.07
Germany	0.62	0.46	0.16	0.91	0.78	0.13	0.11	0.07	0.04
Greece	0.56	0.53	0.03	0.90	0.88	0.02	0.11	0.06	0.06
Hungary	0.55	0.47	0.08	0.85	0.75	0.11	0.05	0.02	0.03
Ireland	0.40	0.36	0.04	0.83	0.76	0.08	0.11	0.08	0.03
Italy	0.54	0.44	0.10	0.90	0.81	0.09	0.15	0.09	0.06
Luxembourg	0.54	0.45	0.08	0.80	0.68	0.12	0.17	0.13	0.03
Netherlands	0.65	0.52	0.12	0.90	0.78	0.13	0.04	0.03	0.01
Norway	0.71	0.61	0.10	0.93	0.82	0.11	0.12	0.08	0.04
Poland	0.38	0.25	0.13	0.81	0.66	0.15	0.05	0.01	0.04
Portugal	0.61	0.53	0.09	0.83	0.72	0.12	0.08	0.03	0.05
Slovak Republic	0.49	0.47	0.02	0.81	0.73	0.08	0.04	0.02	0.01
Slovenia	0.44	0.33	0.11	0.81	0.70	0.10	0.05	0.02	0.02
Spain	0.58	0.48	0.10	0.87	0.80	0.08	0.30	0.18	0.13
Sweden	0.74	0.65	0.09	0.95	0.87	0.08	0.08	0.07	0.01
Switzerland	0.62	0.48	0.14	0.75	0.60	0.15	0.08	0.05	0.03
United Kingdom	0.56	0.46	0.11	0.82	0.68	0.14	0.06	0.03	0.02

The variables are: 1) Closeness to a political party 2) Voted in last national elections, and 3) whether the respondent had taken part in lawful public demonstration during the last 12 months. Data comes from the ESS (waves 1 to 9).

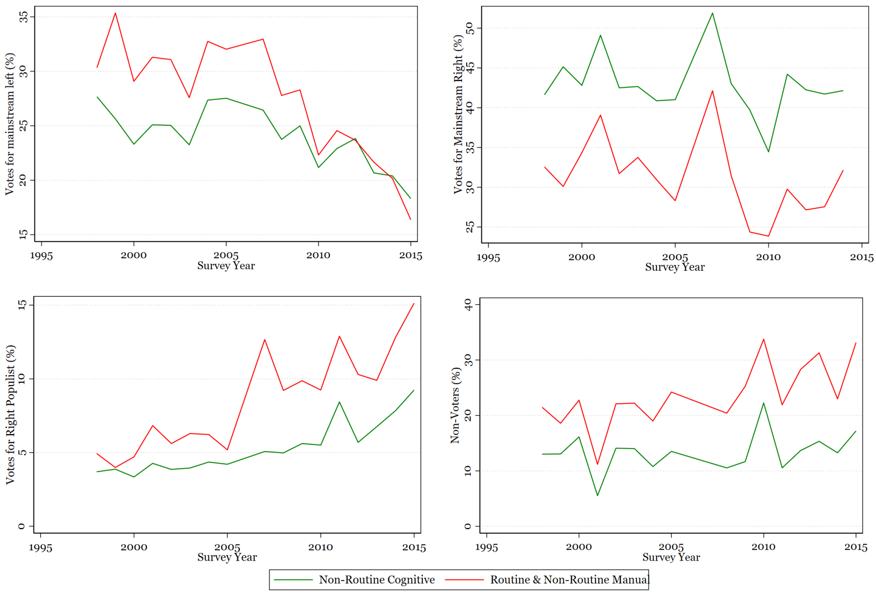


Figure 11: Electoral consequences
Note: Countries included: Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, Italy and United Kingdom. Source: ISSP

Computing and Convergence Diagnostic[22]

I estimate the models using the library *rstanarm* from R. My models converged using stan default configuration.[23] This implied that it considers 2000 iterations, and the first 1000 iterations were removed as a warm-up, then the model was established. I also employ the default target acceptance rate *adapt delta* (δ equal 0.8). In what follows, I present traceplots of the MCMC chains (4) and $\hat{R}$ to monitor the convergence of the parameters.

Figures 12 and 13 present the traceplots for the main model which is the multi-level model with varying intercept and control variables when the independent variable was approached following Frey and Osborne (2017).[24] The y-axis represents the coefficient estimated, and the x-axis the number of iterations. The colors of the lines represent the different chains. A good traceplot would be one in which it is hard to distinguish one chain from another one. In other words, one in which there are different values estimated for the parameters. In this case, the plots show that the model converged since the chains mix very well.

Additionally, to complement the graphical evaluation of the model, I look at the distribution of *Rhat* Gelman-Rubin, which is a convergence diagnostic. When $\hat{R}$ is around 1.00 indicates that the chain has converged, thus, we can trust the samples and chains of the model without drawing more iterations or changing the model. Figure 20 from the Appendix shows the $\hat{R}$ for the model

[22]The Online Appendix contains all the diagnostics per each of the models estimated.
[23]Note that I also estimate the model using *brms*. As expected, the models converged, and the results remain the same.
[24]Figures 29, 30, 34, and 35 present the convergence diagnostic using as the independent variable RTI and a dummy for routine respectively.

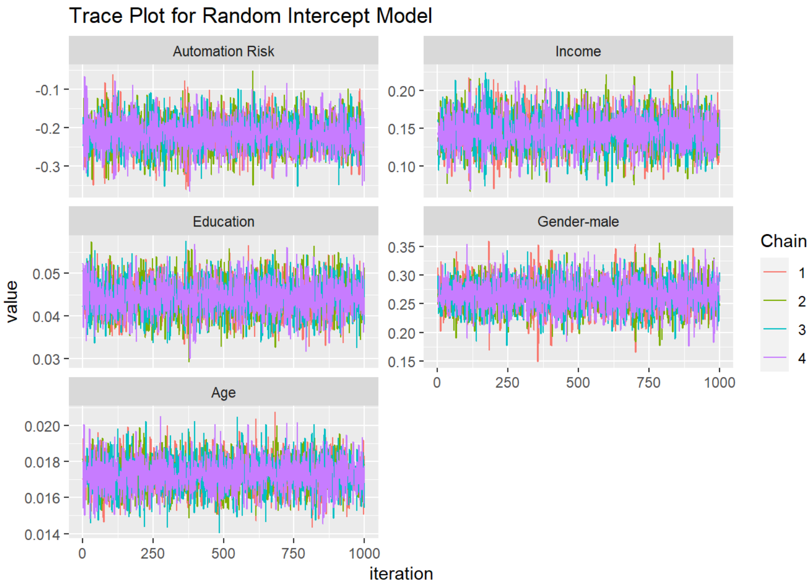


Figure 12: MCMC chains
Note: Trace Plot for the Bayesian Hierarchical Model varying Intercepts, and with the independent variable approached following Frey and Osborne (2017)

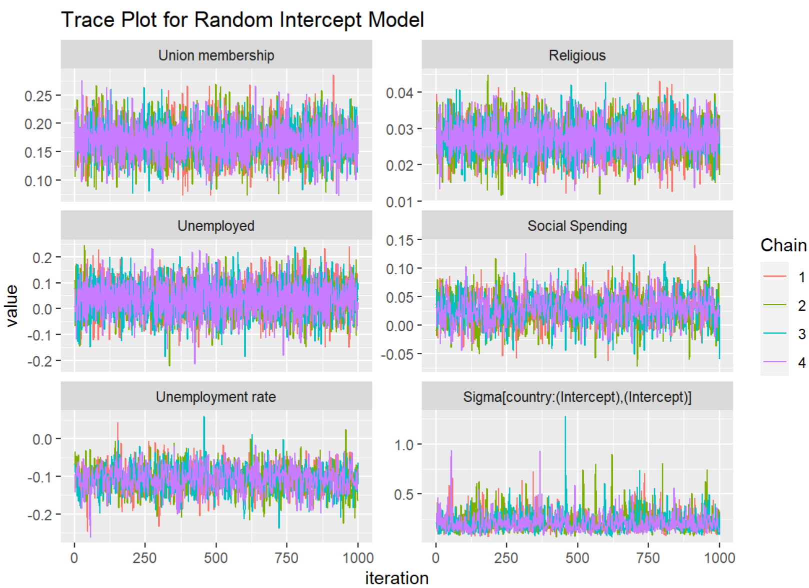


Figure 13: MCMC chains
Note: Trace Plot for the Bayesian Hierarchical Model varying Intercepts, and with the independent variable approached following Frey and Osborne (2017)

goes from 0.999 to 1.006, with a mean of 1.002. Therefore, the model seem to have converged, and fit well.

Model specification

Model specification without varying intercept neither slope - Logit.

$$y_i \sim \text{Binomial}(1, p_i)$$

$$log(p_i) = \alpha_{j[i]} + \beta X_i + \gamma Z_{j[i]}$$

$$\alpha_j \sim N(0, 2.5)$$

$$\beta \sim \text{Normal}(0, 2.5)$$

$$\gamma \sim \text{Normal}(0, 2.5)$$

Model specification with varying intercept and varying slope.

$$y_i \sim \text{Binomial}(1, p_i)$$

$$log(p_i) = \beta_1 \text{Automation Risk} + \lambda X_i + \gamma Z_{j[i]} + \alpha_{0,j[i]} + \alpha_{1,j[i]} \text{Automation Risk}$$

$$\alpha_j \sim N(0, \Sigma_\alpha)$$

$$\Sigma_\alpha \sim \text{decov}(1, 1, 1)$$

where $\alpha_j^T = [\alpha_{0,j}, \alpha_{1,j}]$. Then λ is the vector of coefficients associated with the individual level control variables included at X, and γ does the same for Z

Model Comparison

For the purpose of model comparison, I calculate the information criterion *WAIC* which looks at the variance of the log-likelihood over the posterior draws for each estimation, and includes a penality term. I estimated the it using the WAIC code and also the *Leave-One-Out Cross-Validation* for *elpd*, and the interpretation were the same. The WAIC is defined as follow:

$$WAIC(y, \Theta) = -2(\text{lppd} - \sum_i \text{var}_\theta \text{log} p(y_i|\Theta_s))$$

where $lppd(y, \Theta)$ is $\sum_i \log \frac{1}{S} \sum_s p(y_i|\Theta_s)$, S is the number of samples and Θ is the s-th set of sampled parameter values in the posterior distribution. The lower (higher) the WAIC (elpd), the better the model performed.

Figure 14 presents the models with the same specification in terms of the variables included. That is, all the models have my key independent variable approached using Frey and Osborne's measure and control variables. The difference among these models is that the first one is a Bayesian logistic model that does not include varying intercept by country. Then, I estimated the information criterion parameter for the model varying intercepts and also intercept and slope clustered by country.

From this evaluation, I conclude that the models that include random intercepts or random intercepts and varying slopes fit better than the model without varying intercepts. I also estimated

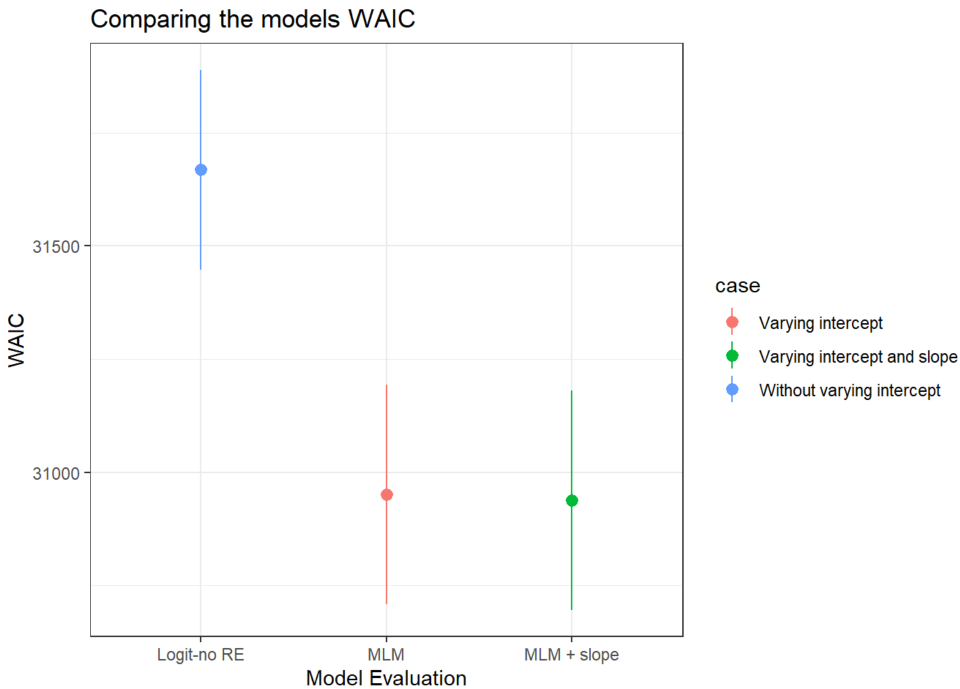


Figure 14: WAIC
Note: The independent variable of these models is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

the WAIC for the model without control variables, but since its value was too large (41.191), it did not allow us to compare the other models very well.[25]

Overall, I conclude that the model that includes control variables and allows intercept to vary has the best fit. I also recognize that the information criterion for the models varying intercept and both –intercept and slope– are very similar. Nevertheless, for theoretical reasons, I argue that the best model is the one that only allows the variation of intercepts since the variation seems to come for the different intercepts, but less from the variation of effects across the automation risks (see for example Table 2). Further theoretical reasons are needed for preferring the model of varying effect by countries for the probability of being automated.

[25]See Figure 21 from the Appendix that includes the four models.

Independent variable: Probability of computarisation Frey and Osborne (2017)

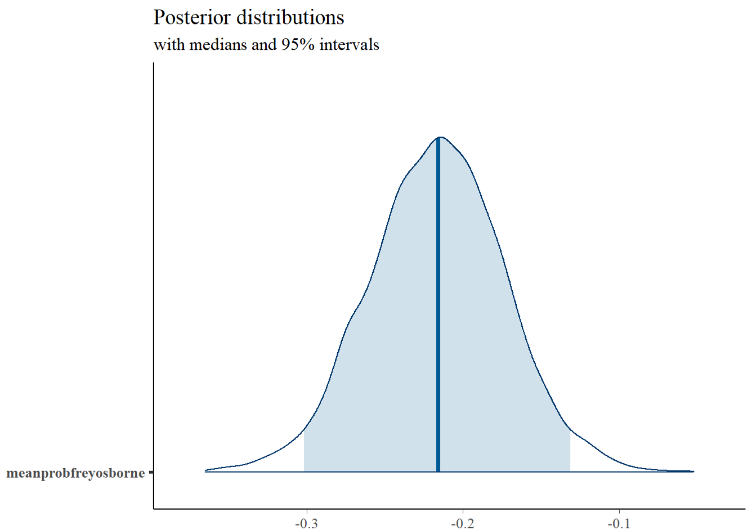


Figure 15: Posterior distribution for Automation risks, MLM model with control variables.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017).

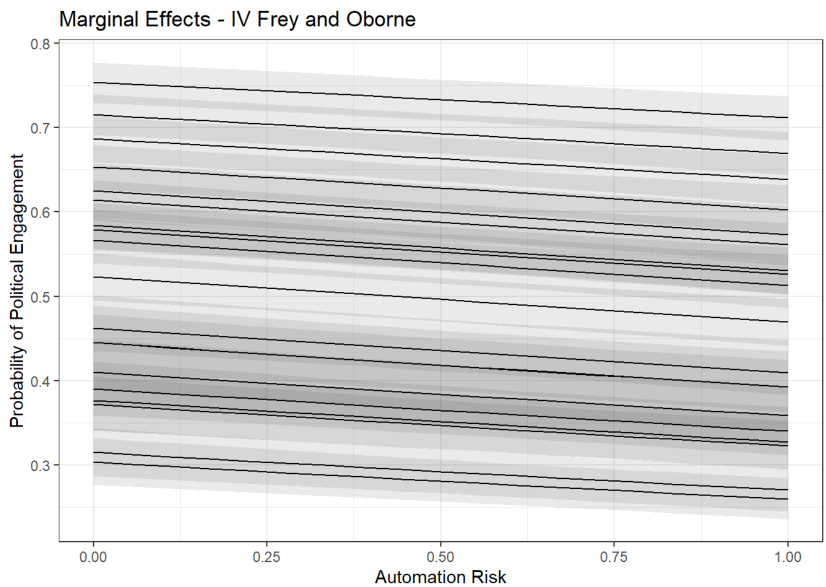


Figure 16: Marginal effects keeping covariates at their observable values, MLM model.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017).

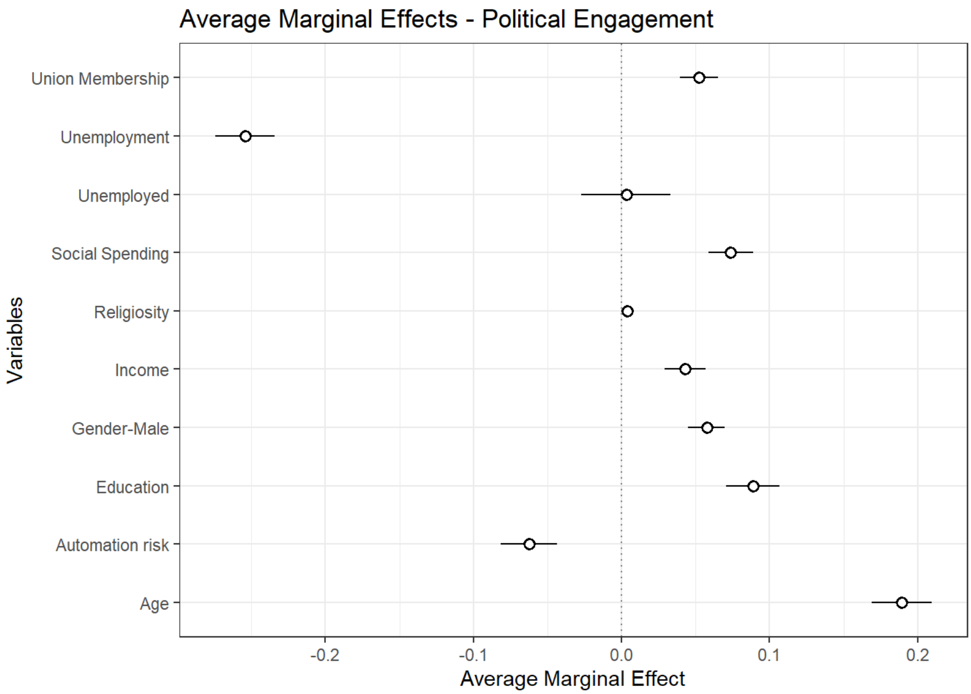


Figure 17: Average marginal effects keeping covariates at their observable values, MLM model. Continuous variables estimated at the percentile 10th and 90th.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017).

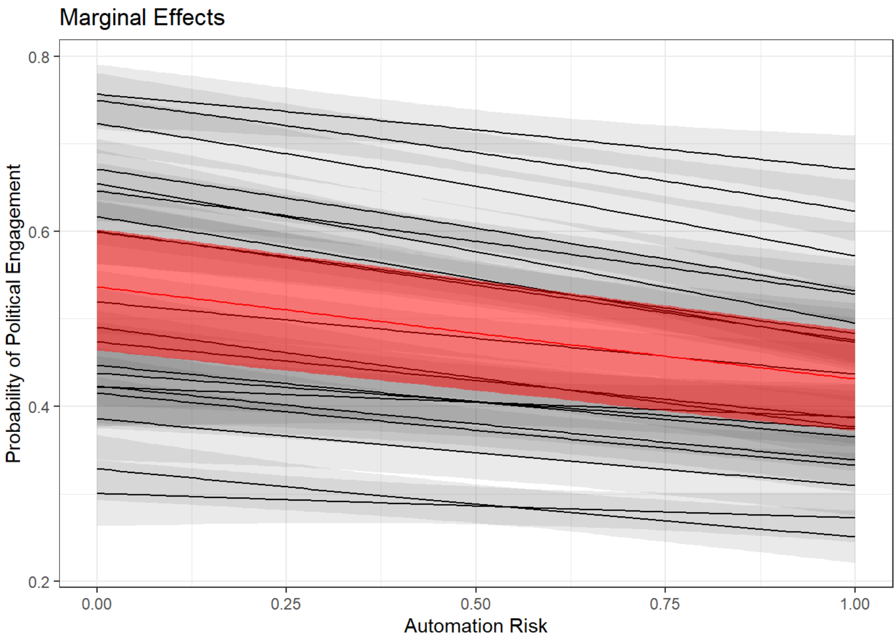


Figure 18: Marginal effects for Bayesian Logistic Hierarchical model varying intercepts and slope for automation risks by country. Model without controls.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017).

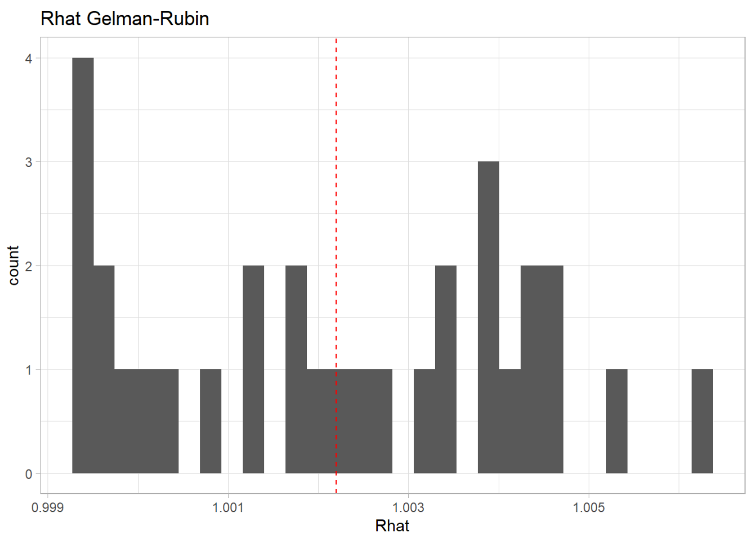


Figure 20: Rhat Gelman-Rubin, for the Bayesian logistic hierarchical model with explanatory variables
Note: The dependent variable of the model is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

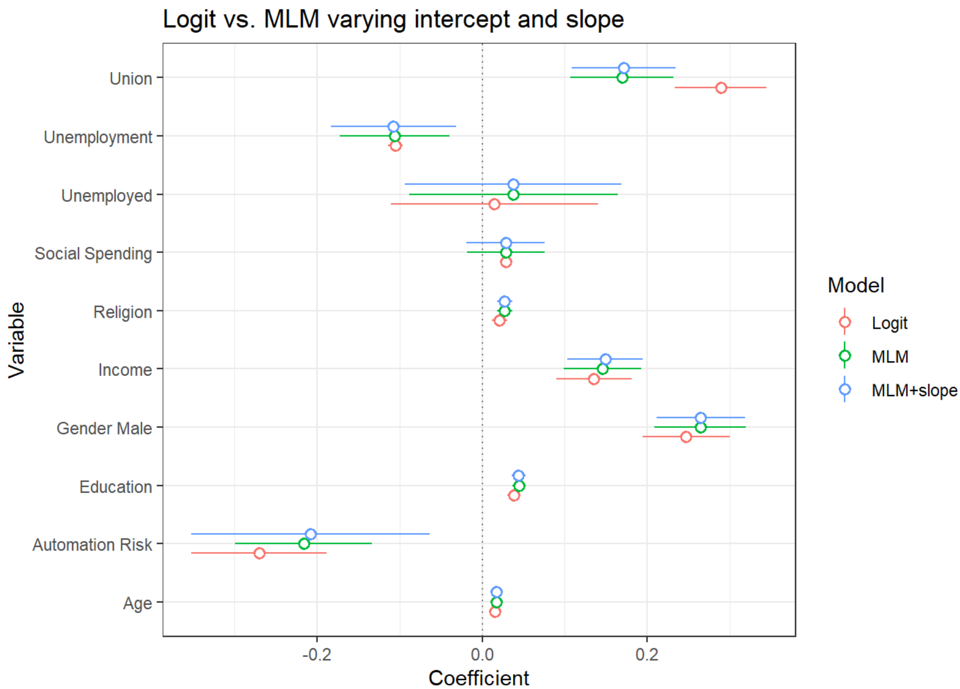


Figure 19: Odd-ratios for Bayesian logistic model without varying intercepts, varying intercepts by country (MLM), and varying both intercept and slope
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

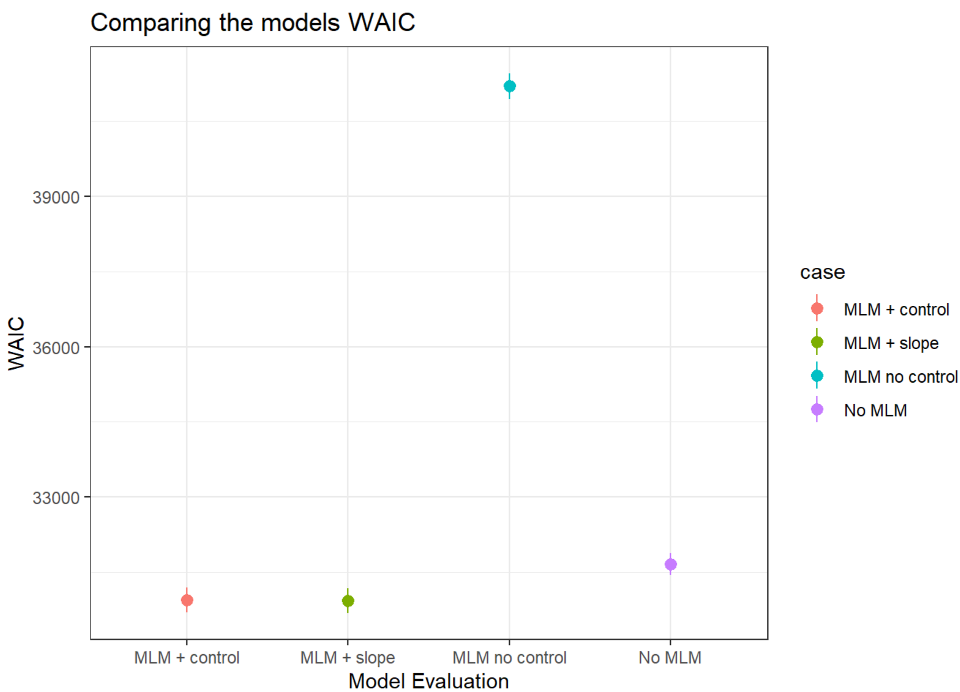


Figure 21: WAIC
Note: The independent variable of these models is exposure to automation approached following Frey and Osborne (2017). Data comes from the 6th wave of the ESS.

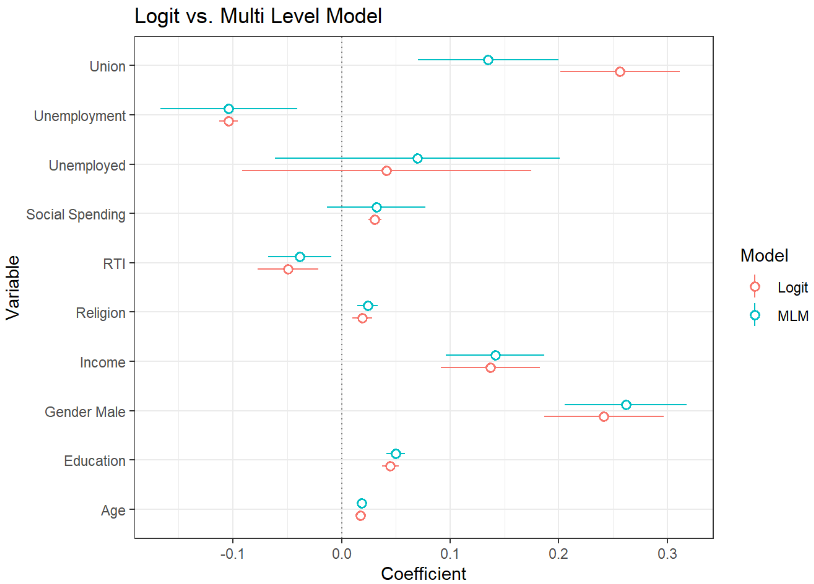


Figure 23: Odd-ratios for Bayesian logistic model without varying intercepts, and varying intercepts by country (MLM)
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

Indepdendent variable: RTI

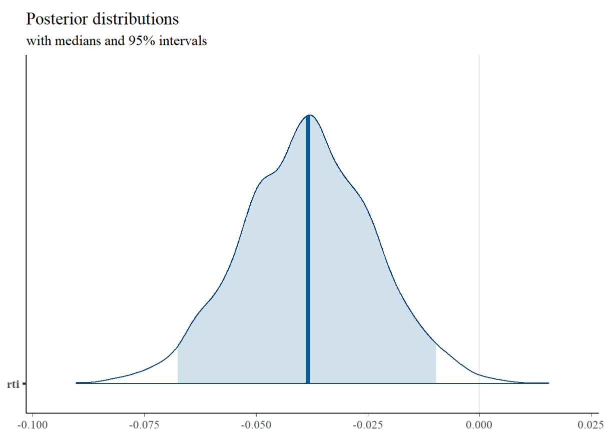


Figure 22: Posterior distribution for RTI index, MLM model with control variables.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached through the RTI index following Goos, Manning, and Salomons (2014).

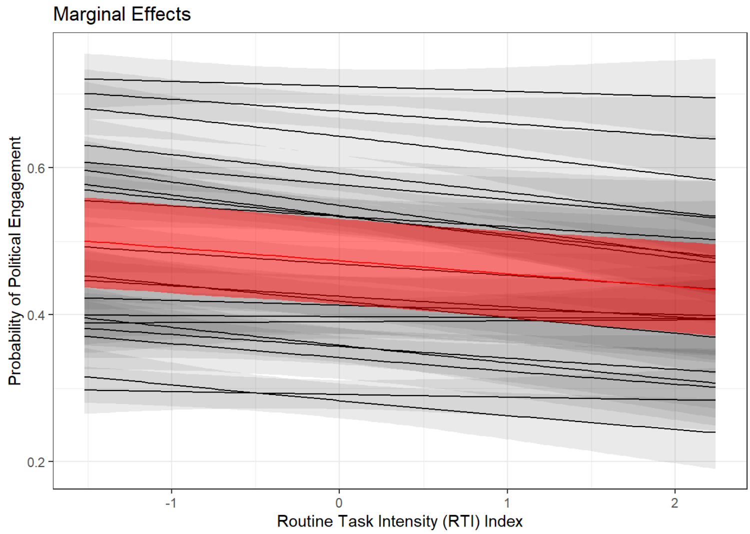


Figure 25: Marginal effects for Bayesian Logistic Hierarchical model varying intercepts and slope for automation risks by country. Model without controls.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

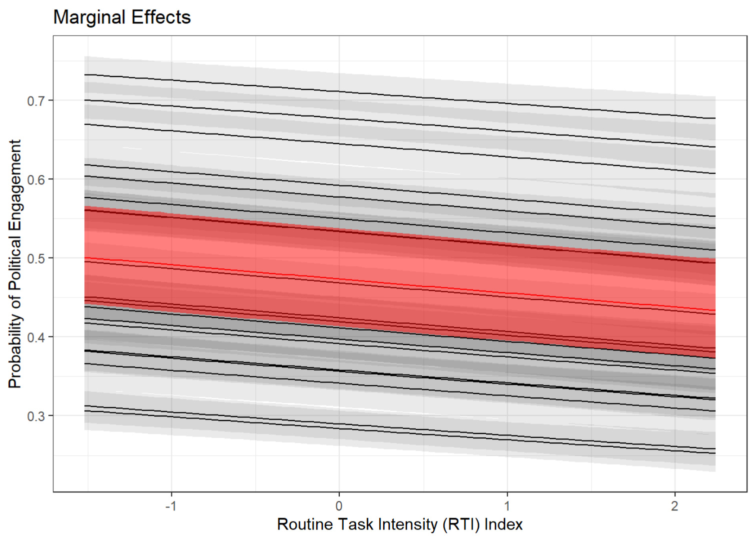


Figure 24: Marginal effects for Bayesian logistic model without additional explanatory variables
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached through the RTI index following Goos, Manning, and Salomons (2014). Data comes from the 6th wave of the ESS.

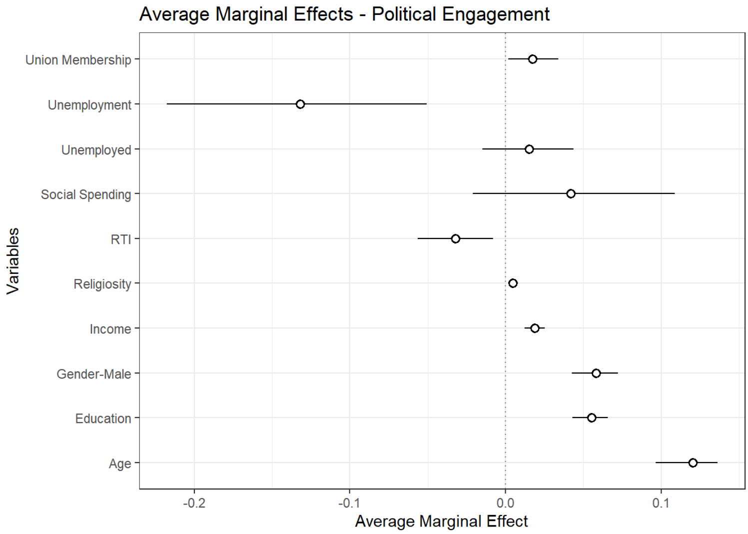


Figure 27: Average marginal effects keeping covariates at their observable values, MLM model. Continuous variables estimated at the percentile 25th and 75th.
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

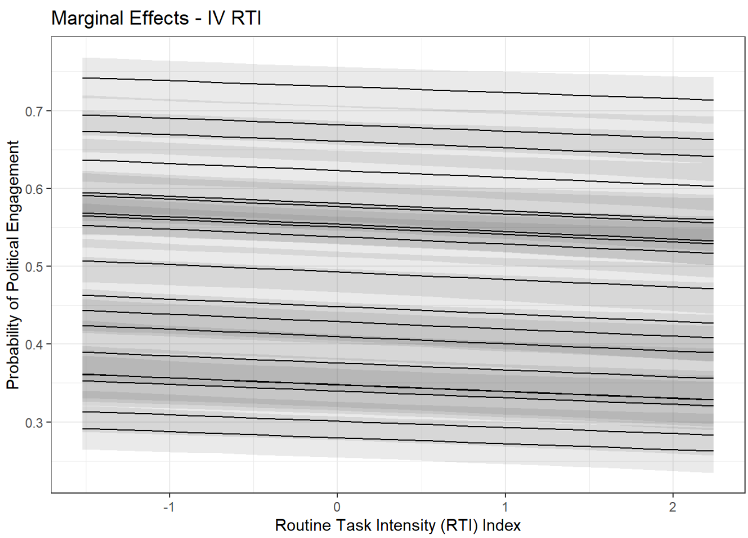


Figure 26: Marginal effects correspond to the model with control variables. Covariates at their observable values
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

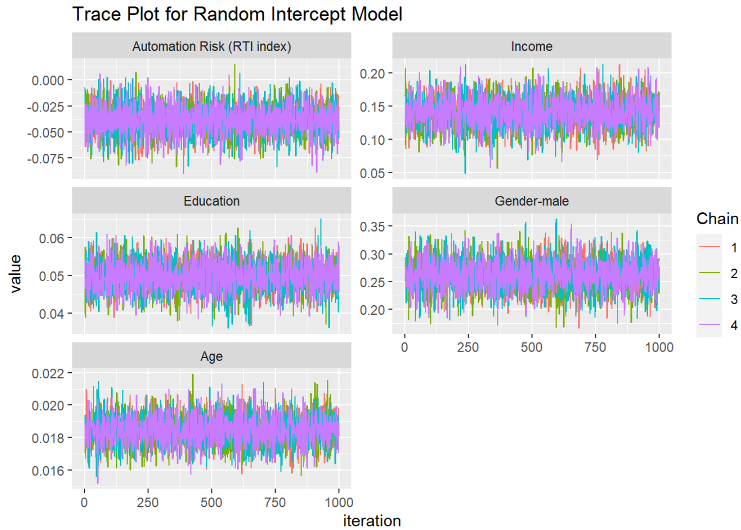


Figure 29: MCMC
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

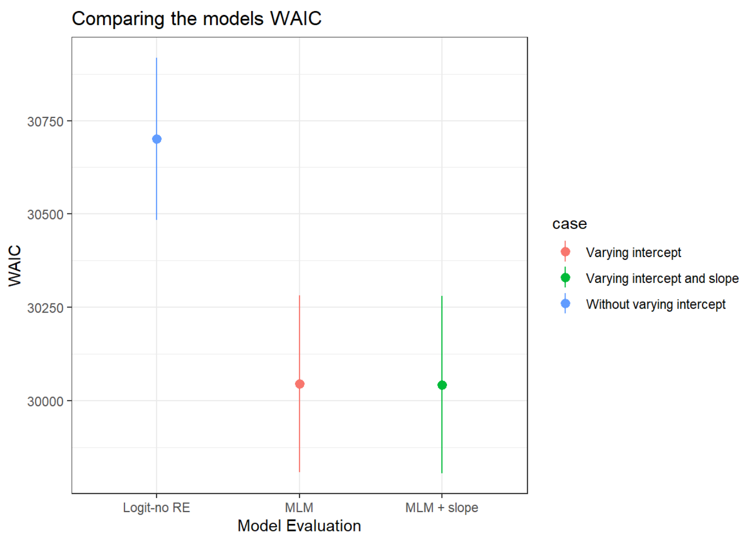


Figure 28: WAIC
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

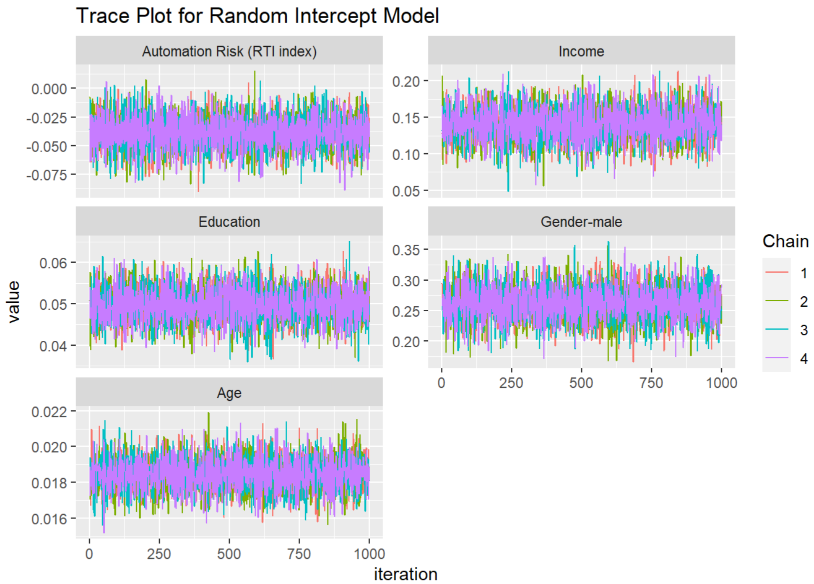


Figure 30: MCMC
Note: The dependent variable is political engagement, and the independent variable is exposure to automation approached following through the RTI index following Goos, Manning, and Salomons (2014).

Indepdendent variable: Dummy Routine

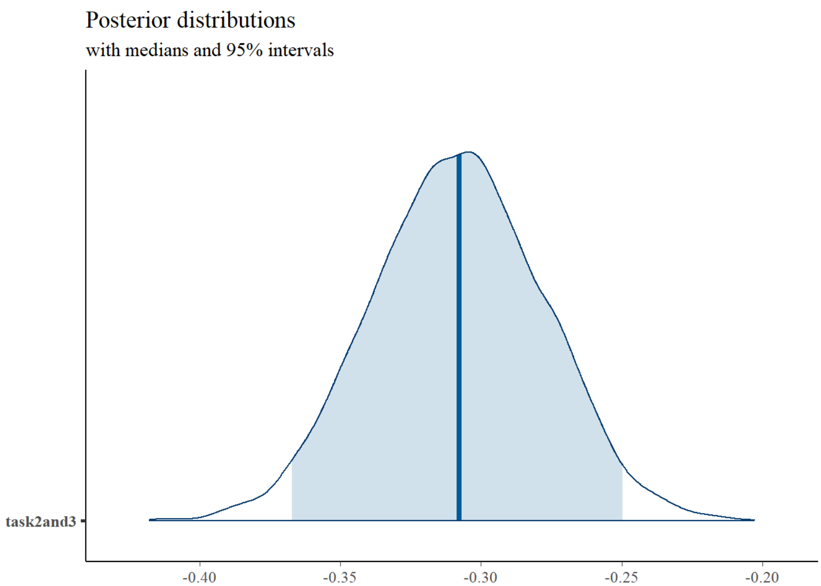


Figure 31: Posterior distribution for Routine dummy, MLM model with control variables
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

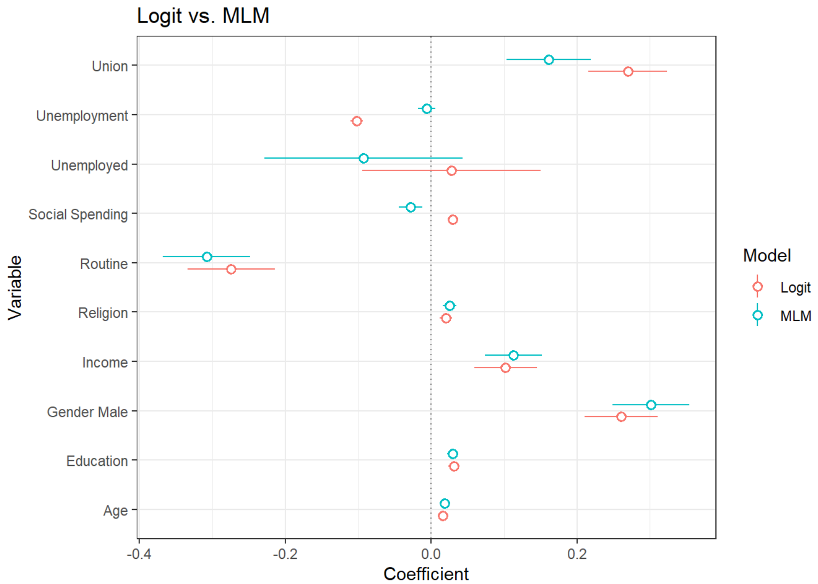


Figure 32: Odds-ratio
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

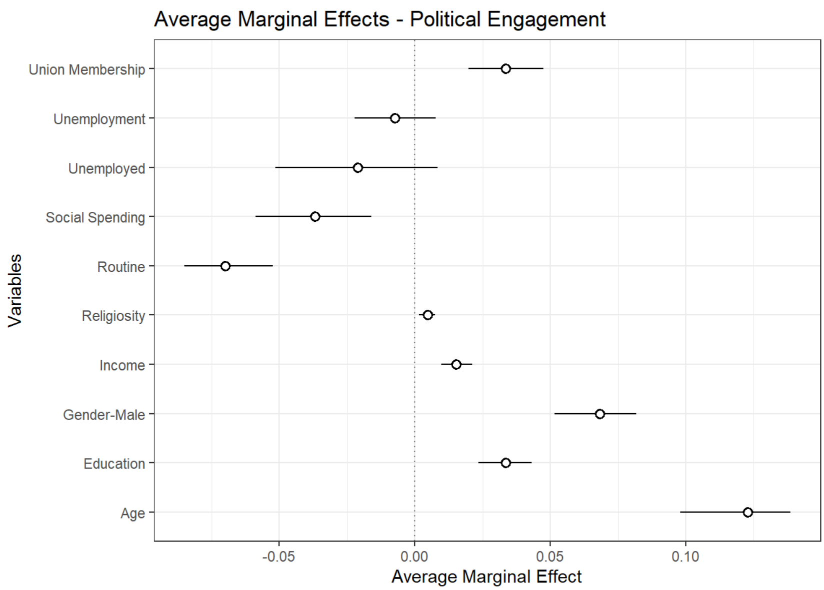


Figure 33: Average marginal effects, covariates at their observable values.
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

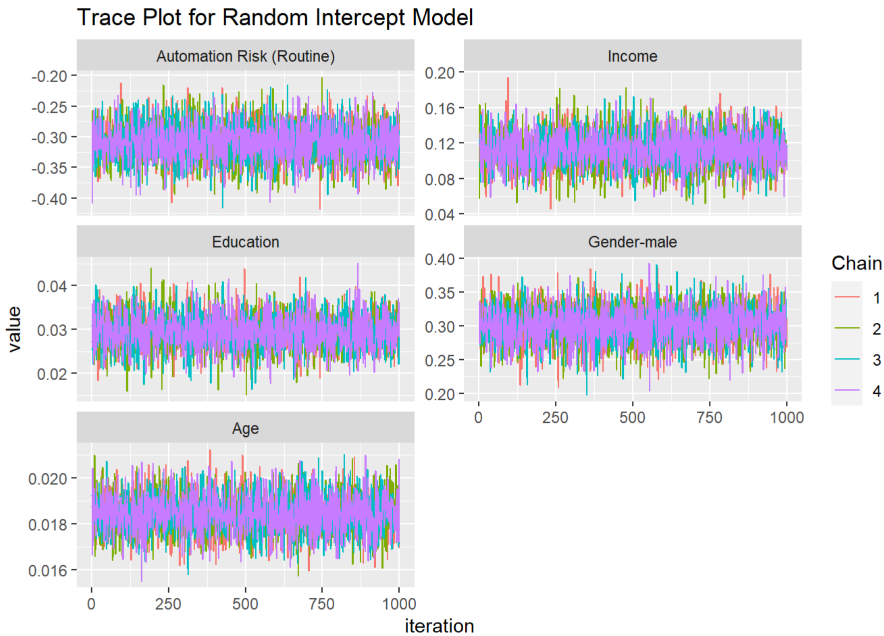


Figure 34: MCMC
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

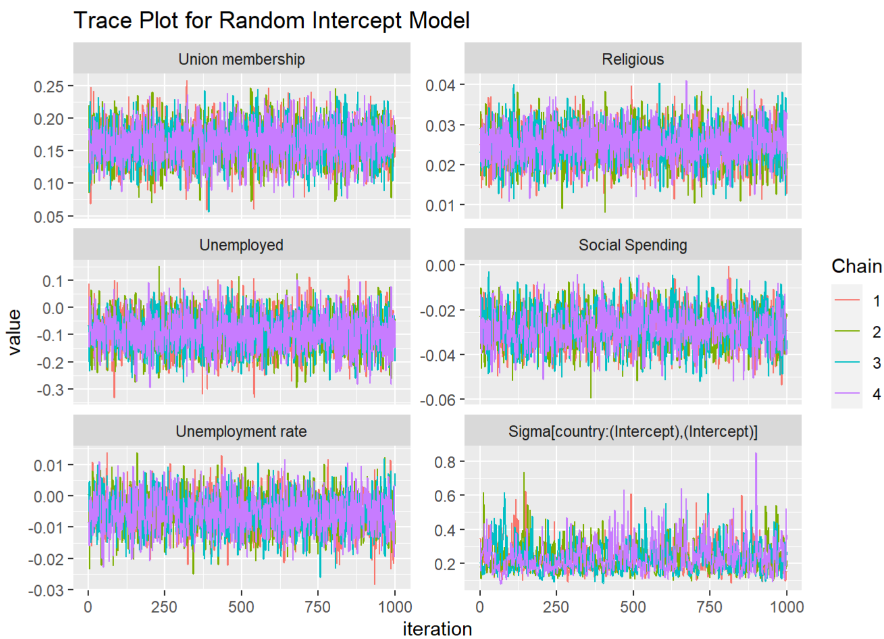


Figure 35: MCMC
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

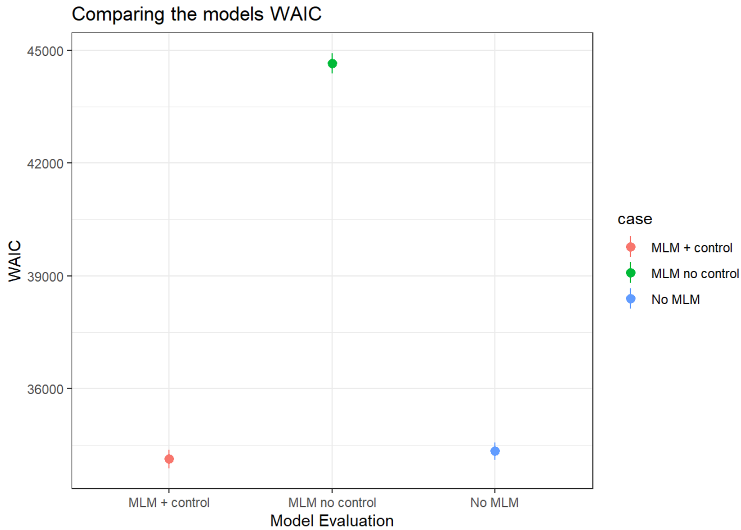


Figure 36: WAIC
Note: The dependent variable is political engagement, and the independent variable is a dummy for routine following Autor, Levy, and Murnane (2003)

Multilevel Model with waves 1-9

TABLE 3: Multilevel analaysis - Political Engagement

	(1)	(2)	(3)	(4)	(5)	(6)
Political Engagement						
Automation Risk	-0.140***	-0.120***	-0.075***	-0.071***	-0.062***	-0.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Demographic		✓	✓	✓	✓	✓
Socio-econ				✓	✓	✓
Labor regulations					✓	✓
Politics						✓
N	89606	89606	89606	72028	37428	37428

Dependent variable: whether respondents feel closer to a particular party. Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. *p*-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 4: Multilevel analaysis - Automation and Turnout

	(1)	(2)	(3)	(4)	(5)	(6)
Turnout						
Automation Risk	-0.112***	-0.094***	-0.049***	-0.050***	-0.057***	-0.057***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Demographic		✓	✓	✓	✓	✓
Socio-econ				✓	✓	✓
Labor regulations					✓	✓
Politics						✓
N	85092	85092	85092	68451	35892	35892

Dependent variable: whether respondents participated in past elections (turnout). Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. *p*-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 5: Multilevel analysis - Protest

	(1)	(2)	(3)	(4)	(5)	(6)
Protest						
Automation Risk	-0.051***	-0.050***	-0.028***	-0.024***	-0.020***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Demographic		✓	✓	✓	✓	✓
Socio-econ				✓	✓	✓
Labor regulations					✓	✓
Politics						✓
N	90393	90393	90393	72677	37785	37785

Dependent variable: whether respondents have taken part in lawful public demonstration last year. Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6: Multilevel analaysis - Political Engagement

	(1)	(2)	(3)	(4)	(5)	(6)
Automation Risk	-0.140***	-0.120***	-0.075***	-0.071***	-0.062***	-0.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income		0.046***	0.029***	0.024***	0.027***	0.027***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education			0.010***	0.009***	0.009***	0.009***
			(0.000)	(0.000)	(0.000)	(0.000)
Male			0.055***	0.054***	0.048***	0.048***
			(0.000)	(0.000)	(0.000)	(0.000)
Age			0.005***	0.005***	0.005***	0.005***
			(0.000)	(0.000)	(0.000)	(0.000)
Union membership			0.041***	0.044***	0.036**	0.036**
			(0.000)	(0.000)	(0.017)	(0.017)
Religious			0.006***	0.005***	0.007***	0.007***
			(0.000)	(0.000)	(0.000)	(0.000)
Unemployed			-0.021**	-0.012	-0.024**	-0.024**
			(0.035)	(0.238)	(0.021)	(0.020)
Lag social spending				-0.006***	-0.004**	-0.003**
				(0.002)	(0.036)	(0.030)
Openess				-0.001	-0.000	0.000
				(0.211)	(0.933)	(0.952)
GDP growth				0.008*	0.003***	0.003***
				(0.073)	(0.006)	(0.004)
Foreign Born Rate				-0.004***	-0.006***	-0.006***
				(0.000)	(0.000)	(0.000)
LMP					-0.012	-0.011
					(0.528)	(0.612)
Unemployment rate					-0.006	-0.007
					(0.164)	(0.143)
EPL					0.112***	0.114***
					(0.000)	(0.000)
Union coverage					0.001	0.001
					(0.256)	(0.150)
Industrial strikes					-0.000	-0.000
					(0.345)	(0.272)
Federalism						0.040
						(0.364)
PR						-0.025
						(0.589)
_cons	0.610***	0.549***	0.138***	0.403***	0.052	0.058
	(0.000)	(0.000)	(0.001)	(0.000)	(0.619)	(0.472)
lns1_1_1 _cons	-2.471***	-2.468***	-2.496***	-2.265***	-2.495***	-2.558***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnsig_e _cons	-0.718***	-0.720***	-0.732***	-0.737***	-0.744***	-0.744***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	89606	89606	89606	72028	37428	37428

Dependent variable: whether respondents feel closer to a particular party. Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. *p*-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7: Multilevel analaysis - Automation and Turnout

	(1)	(2)	(3)	(4)	(5)	(6)
Automation Risk	-0.112***	-0.094***	-0.049***	-0.050***	-0.057***	-0.057***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Income		0.042***	0.023***	0.018***	0.016***	0.016***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Years of education			0.010***	0.009***	0.009***	0.009***
			(0.000)	(0.000)	(0.000)	(0.000)
Male			-0.003	-0.004	-0.003	-0.003
			(0.528)	(0.414)	(0.710)	(0.709)
Age			0.005***	0.006***	0.006***	0.006***
			(0.000)	(0.000)	(0.000)	(0.000)
Union membership			0.045***	0.051***	0.044***	0.044***
			(0.000)	(0.000)	(0.000)	(0.000)
Religious			0.005***	0.005***	0.007***	0.006***
			(0.001)	(0.002)	(0.001)	(0.001)
Unemployed			-0.098***	-0.079***	-0.106***	-0.106***
			(0.000)	(0.000)	(0.000)	(0.000)
Lag social spending				-0.004*	0.000	0.000
				(0.062)	(0.916)	(0.806)
Openess				-0.001***	-0.000	-0.000
				(0.007)	(0.523)	(0.550)
GDP growth				0.001	0.000	0.000
				(0.562)	(0.852)	(0.832)
Foreign Born Rate				-0.005***	-0.006***	-0.006***
				(0.000)	(0.000)	(0.000)
LMP					-0.015	-0.015
					(0.271)	(0.282)
Unemployment rate					0.002	0.001
					(0.658)	(0.694)
EPL					0.099***	0.096***
					(0.000)	(0.000)
Union coverage					0.001**	0.001**
					(0.044)	(0.044)
Industrial strikes					0.000**	0.000**
					(0.035)	(0.029)
Federalism						0.010
						(0.719)
PR						0.018
						(0.626)
_cons	0.873***	0.816***	0.419***	0.628***	0.209***	0.182***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.001)
lns1_1_1 _cons	-2.459***	-2.465***	-2.567***	-2.393***	-2.465***	-2.502***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnsig_e _cons	-0.988***	-0.992***	-1.015***	-1.012***	-1.021***	-1.021***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	85092	85092	85092	68451	35892	35892

Dependent variable: whether respondents whether respondents participated in past elections (turnout). Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 8: Multilevel analysis - Protest

	(1)	(2)	(3)	(4)	(5)	(6)
Automation Risk	-0.051***	-0.050***	-0.028***	-0.024***	-0.020***	-0.020***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Income		0.002	-0.004**	-0.004**	-0.003	-0.003
		(0.554)	(0.013)	(0.025)	(0.193)	(0.192)
Years of education			0.006***	0.005***	0.004***	0.004***
			(0.000)	(0.000)	(0.001)	(0.001)
Male			-0.001	-0.002	-0.006	-0.006
			(0.843)	(0.560)	(0.233)	(0.232)
Age			-0.000	-0.000	-0.000	-0.000
			(0.134)	(0.664)	(0.218)	(0.218)
Union membership			0.058***	0.059***	0.048***	0.048***
			(0.000)	(0.000)	(0.001)	(0.001)
Religious			-0.004***	-0.004***	-0.002**	-0.003**
			(0.001)	(0.003)	(0.027)	(0.026)
Unemployed			0.009*	0.007	0.011	0.011
			(0.070)	(0.188)	(0.158)	(0.156)
Lag social spending				0.001	0.001	0.001
				(0.367)	(0.684)	(0.614)
Openess				-0.000	-0.001***	-0.001**
				(0.917)	(0.009)	(0.011)
GDP growth				-0.000	-0.001	-0.001
				(0.786)	(0.473)	(0.532)
Foreign Born Rate				-0.001***	-0.001	-0.001
				(0.004)	(0.392)	(0.380)
LMP					-0.015	-0.016
					(0.317)	(0.286)
Unemployment rate					0.001	0.001
					(0.394)	(0.363)
EPL					-0.002	-0.001
					(0.928)	(0.959)
Union coverage					-0.001*	-0.001*
					(0.068)	(0.091)
Industrial strikes					-0.000	-0.000
					(0.570)	(0.637)
Federalism						0.048*
						(0.085)
PR						0.028
						(0.473)
_cons	0.121***	0.118***	0.035***	0.028	0.186**	0.105
	(0.000)	(0.000)	(0.001)	(0.511)	(0.037)	(0.201)
lns1_1_1 _cons	-2.936***	-2.936***	-2.813***	-2.699***	-2.660***	-2.915***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
lnsig_e _cons	-1.280***	-1.280***	-1.288***	-1.302***	-1.387***	-1.387***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
N	90393	90393	90393	72677	37785	37785

Dependent variable: whether respondents have taken part in lawful public demonstration last year. Independent variable is exposure to automation (Frey and Osborne 2017). SEs clustered by country. p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Marginal Effects

Following there is a summary of the average marginal effects. Continuous variables were calculated at 10th and 90th percentile.

TABLE 9: Average marginal effects (AME) for OLS hierarchical model clustered by countries with additional explanatory variables.

	Turnout		***Protest***	
Variable	Margins		Margins	
Unemployed	-0.083	***	0.007	
Unemployment rate	-0.075		0.081	
Automation Risk	**-0.056**	***	**-0.017**	***
Male	0.000		-0.004	
Religious	0.005	***	-0.003	**
Income	0.026	***	-0.004	***
Union Membership	0.042	***	0.032	***
Lag social spending	0.086		-0.037	
Years of Education	0.099	***	0.032	***
Age	0.244	***	-0.009	

The dependent variable is political engagement, and the independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from waves 1-9 of the ESS. AME estimated with other variables at their means.

Robustness Check

TABLE 10: Multilevel analysis - Political Engagement Robustness Check

	(1) Closeness	(2) Closeness	(3) Turnout	(4) Turnout	(5) Protest	(6) Protest
Automation Risk	-0.062^{***}	-0.062^{***}	-0.057^{***}	-0.058^{***}	-0.014^{***}	-0.014^{***}
	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.008)
Demographic	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
Work Regulation	✓	✓	✓	✓	✓	✓
FE Country	✓	✓	✓	✓	✓	✓
FE Year		✓		✓		✓
N	37428	37428	35892	35892	34591	34591

Hierarchical model at country level. SEs clustered by country. The independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from waves 1-9 of the ESS. p-values in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 11: Multilevel analysis - Political Engagement Robustness Checks

	(1) Closeness	(2) Closeness	(3) Turnout	(4) Turnout	(5) Protest	(6) Protest
main						
Automation Risk	-0.064***	-0.061***	-0.057***	-0.056***	-0.015***	-0.013**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)	(0.017)
Offshoring	0.018**		0.024***		0.000	
	(0.034)		(0.004)		(0.975)	
Skill specificity		-0.001		-0.001		-0.001***
		(0.714)		(0.354)		(0.010)
Demographic	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
Work Regulations	✓	✓	✓	✓	✓	✓
N	32841	37422	31458	35886	30373	34591

Hierarchical model at country level. SEs clustered by country. The independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from waves 1-9 of the ESS. *p*-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Moderation Effects of Income and Social Safety Nets

TABLE 12: Multilevel analaysis - Political Engagement

	(1) Closeness	(2) Turnout	(3) Protest	(4) Closeness	(5) Turnout	(6) Protest
Automation Risks	-0.106***	-0.093***	-0.036***	-0.108***	-0.075***	-0.045***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Income	0.0176***	0.00709**	-0.00920***	0.0298***	0.0234***	-0.00371**
	(0.000)	(0.018)	(0.000)	(0.000)	(0.000)	(0.022)
Automation × Income	**0.027*****	**0.038*****	**0.013****			
	(0.000)	(0.000)	(0.012)			
Unionization Rate				-0.000	-0.000	-0.002***
				(0.761)	(0.817)	(0.000)
Automation × Union				**0.001****	**0.001***	**0.001*****
				(0.013)	(0.098)	(0.009)
Demographic	✓	✓	✓	✓	✓	✓
Socio-econ	✓	✓	✓	✓	✓	✓
N	89606	85092	82298	84363	80220	77526

Hierarchical model at country level. SEs clustered by country. The independent variable is exposure to automation approached following Frey and Osborne (2017). Data comes from waves 1-9 of the ESS. *p*-values in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Mediation Analysis

TABLE 13: Table 3: Effects of Risk of automation on Political Engagement (1st stage).

	(1) Sociotropic	(2) Egocentric	(3) Sociotropic	(4) Egocentric	(5) Sociotropic	(6) Egocentric
Automation	-0.241***	-0.102***	-0.241***	-0.102***	-0.241***	-0.102***
	(0.062)	(0.016)	(0.062)	(0.016)	(0.062)	(0.016)
Female	-0.238***	0.014	-0.238***	0.014	-0.238***	0.014
	(0.048)	(0.012)	(0.048)	(0.012)	(0.048)	(0.012)
Age	-0.001	0.003***	-0.001	0.003***	-0.001	0.003***
	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)
Unemployed	-0.366***	-0.224***	-0.366***	-0.224***	-0.366***	-0.224***
	(0.045)	(0.017)	(0.045)	(0.017)	(0.045)	(0.017)
Union Membership	-0.175***	-0.018	-0.175***	-0.018	-0.175***	-0.018
	(0.049)	(0.014)	(0.049)	(0.014)	(0.049)	(0.014)
Income	0.100***	0.126***	0.100***	0.126***	0.100***	0.126***
	(0.009)	(0.003)	(0.009)	(0.003)	(0.009)	(0.003)
Religious	0.062***	-0.003	0.062***	-0.003	0.062***	-0.003
	(0.007)	(0.002)	(0.007)	(0.002)	(0.007)	(0.002)
Regional Unemployment	0.002	-0.001	0.002	-0.001	0.002	-0.001
	(0.017)	(0.004)	(0.017)	(0.004)	(0.017)	(0.004)
Regional Econ Growth	0.003	-0.014**	0.003	-0.014**	0.003	-0.014**
	(0.018)	(0.006)	(0.018)	(0.006)	(0.018)	(0.006)
Foreign Born Rate	-0.012	0.001	-0.012	0.001	-0.012	0.001
	(0.010)	(0.003)	(0.010)	(0.003)	(0.010)	(0.003)
Education	Yes	Yes	Yes	Yes	Yes	Yes
NUTS FE	Yes	Yes	Yes	Yes	Yes	Yes
N	12108	12213	12108	12213	12108	12213
r2_a	0.251	0.324	0.251	0.324	0.251	0.324

The dependent variable of columns 1 and 2 is political engagement, 3 and 4 turnout, and 5 and 6 political protest.

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 14: Table 3: Mediated effects of Risk of automation on Political Engagement (2nd stage).

	(1) Sociotropic	(2) Egocentric	(3) Sociotropic	(4) Egocentric	(5) Sociotropic	(6) Egocentric
Automation Risk	**-0.337*****	**-0.332*****	**-0.496*****	**-0.479*****	**-0.425*****	**-0.417*****
	(0.051)	(0.052)	(0.090)	(0.090)	(0.130)	(0.131)
Sociotropic	0.052***		0.071***		-0.022	
	(0.013)		(0.018)		(0.019)	
Egocentric		0.143***		0.235***		-0.017
		(0.039)		(0.041)		(0.061)
Female	-0.202***	-0.225***	-0.001	-0.025	-0.179**	-0.179**
	(0.044)	(0.044)	(0.052)	(0.053)	(0.071)	(0.072)
Age	0.017***	0.017***	0.024***	0.023***	-0.021***	-0.021***
	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Unemployed	-0.032	-0.025	-0.245***	-0.221***	0.030	0.034
	(0.045)	(0.045)	(0.062)	(0.061)	(0.077)	(0.080)
Union Membership	0.157***	0.156***	0.461***	0.450***	0.795***	0.791***
	(0.047)	(0.046)	(0.074)	(0.073)	(0.112)	(0.111)
Income	0.042***	0.030***	0.151***	0.129***	0.002	-0.001
	(0.008)	(0.009)	(0.014)	(0.014)	(0.017)	(0.018)
Religious	0.021***	0.025***	0.020*	0.025**	0.013	0.013
	(0.008)	(0.007)	(0.012)	(0.012)	(0.013)	(0.013)
Regional Unemployment	-0.009	-0.009	-0.050*	-0.048*	0.051	0.048
	(0.016)	(0.016)	(0.027)	(0.026)	(0.032)	(0.032)
Regional Econ Growth	0.014	0.013	0.006	0.011	0.116***	0.107**
	(0.023)	(0.023)	(0.020)	(0.020)	(0.043)	(0.043)
Foreign Born Rate	-0.009	-0.010	-0.009	-0.009	0.010	0.009
	(0.012)	(0.012)	(0.015)	(0.014)	(0.018)	(0.018)
Education	Yes	Yes	Yes	Yes	Yes	Yes
NUTS FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11947	12047	11382	11464	12092	12196
r2_p	0.040	0.040	0.119	0.119	0.087	0.086

The dependent variable of columns 1 and 2 is political engagement, 3 and 4 turnout, and 5 and 6 political protest.
Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix

Further details about model convergence can be provided by email.