The Path from Automation to Populist Political Behavior

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I investigate the impact of automation exposure on political behavior in post-industrial societies, with a specific focus on support for populism. I examine potential causal mechanisms by exploring the interplay between economic and cultural factors. Using double randomization of treatment and mediators in a survey experiment conducted in the US, I divide my sample into two groups: one is randomly assigned to either a treatment condition related to exposure to robots or AI replacing jobs, or a control condition related to technological development; the other experiences manipulation of both the treatment and the encouragement of mediators (marginalization and nostalgia). My findings reveal that feelings of marginalization and nostalgia mediate the effects of job-threatening technological change on support for populism and illiberal policies. To enhance external validity, I implement mediation analysis using survey data from the European Social Survey. The results help us understand why at-risk workers turn to radical right parties.

Keywords: automation, populism, cultural grievances, nostalgia, marginalization.

In recent years, the rise of automation and technological change has led to significant transformations in the way tasks are performed by workers, resulting in widespread discussions and concerns regarding the future of work. Prominent headlines such as "AI Poses 'Risk of Extinction,' Industry Leaders Warn"[1] and "AI and the future of work: Everything is about to change",[2] underscore the growing awareness of the potential risks associated with the rapid pace of automation. Studies by Acemoglu and Restrepo (2022) estimate that technological advancement accounts for 50-70 percent of changes in the US wage structure, while Frey and Osborne (2017) predict that automation will displace 47 percent of jobs in the US over the next two decades, predominantly affecting middle-wage workers. These transformations have contributed to the rise of labor market polarization, increasing income inequality, and the erosion of the middle class. This economic process is therefore likely to have dramatic political effects.

While scholars have made significant progress in investigating the political consequences of technological change, the majority of these discussions have primarily focused on economic factors. Existing research has extensively documented the link between individuals adversely affected by automation and their tendency to oppose the prevailing status quo and support the radical right (e.g., Frey, Berger, and Chen, 2017; Owen, 2019; Gingrich, 2019; Im et al., 2019; Milner, 2021; Kurer and Palier, 2019; Autor et al., 2020). Additionally, support for the establishment and the status quo has been observed among those who benefit from technological advancements (Gallego, Kurer, and Scholl, 2021). However, only a few notable exceptions have explored non-material consequences, such as the impact of technological change on social status (Kurer, 2020) and attitudes towards immigration (Gamez-Djokic and Waytz, 2020; Kaihovaara and Im, 2020; Wu, 2022*a*,*b*). In this study, I ask how, and to what extent, exposure to automation risk affects support for populism and illiberal policy preferences. I argue that cultural grievances play a crucial role in understanding the consequences of this economic shock.

I theorize that this shift to the right occurs due to increased cultural grievances triggered by automation, one of the primary drivers of structural change in the labor market since the mid-1990s.[3] Unlike other economic threats, automation represents a long-term replacement shock. Citizens have taken notice of this threat, as evidenced by a Eurobarometer survey in

[1] New York Times, May 30, 2023.
[2] CNN, Mar 19, 2023
[3] Data from the International Federation of Robotics (IFR) documents an abrupt rise in the stock of (industrial) robots in the United States and Western Europe (see Figure A.1).

which three-quarters of Europeans expressed the belief that robots and artificial intelligence are taking away people's jobs in significant numbers (Eurobarometer, 2017). While automation does generate threats, it also improves the safety and productivity of certain jobs, making this phenomenon even more complex to unpack. A respondent to my survey succinctly captured this trade-off, stating, "Technology at times can be a blessing and a curse. In my experience it at times has made some jobs easier, at other times it has put people out of work. I've liked what technology has done for me at work, but I also know it's only a few steps away from being able to do my job so I like and dislike these devices."[4]

This paper argues that job-threatening technological advancements lead to cultural grievances, which can be observed through feelings of marginalization and nostalgia. These emotions serve as coping mechanisms to mitigate the insecurity arising from significant structural changes in the labor market. Scholars have previously linked periods of significant economic change with individuals' nativism and a sense of existential or societal threats (Barauskaitė, Gineikienė, and Fennis, 2022; Routledge et al., 2008; Goldstein and Peters, 2014; Bukowski et al., 2017), diminishing prosocial feelings (Granulo, Fuchs, and Puntoni, 2019; Festinger, 1954), triggering outgroup threats (Brader, Valentino, and Suhay, 2008), or evoking nostalgia (Zhou et al., 2013). Automation disrupts job opportunities and stability, resulting in personal and societal insecurities when individuals compare themselves to others. Consequently, these insecurities may be expressed as sentiments of marginalization and a yearning for the past. Vulnerable individuals, adopting such symbolic attitudes, become more susceptible to the influence of candidates who endorse prejudice against minorities, advocate for anti-elitism, and employ nostalgic rhetoric—all of which are prevalent characteristics among populist leaders.

Understanding the impact of this economic phenomenon on political behavior is not a simple task, extending beyond a mere juxtaposition of economic and cultural variables. This article demonstrates the significance of both factors and highlights their interplay. I do this by linking automation and changes in symbolic attitudes and then connecting these relationships with political behavior through a multimethod approach comprising a design-based experimental analysis with a double randomization survey experiment (manipulation of the treatment and encouragement of mediators) conducted in the US, along with model-based or measurement-of-mediation designs on observational survey data from thirteen European countries.

[4]Another example of a similar response: "I like the ease of work that is created through technology, but I see it quickly replacing so many jobs. It has been fun while it lasted though."

My analysis yields nuanced findings. First, I present compelling evidence that individuals exposed to the automation of jobs treatment (involving robots or AI), as opposed to a more neutral technological context, display a higher propensity for holding populist attitudes, particularly anti-elitism, and exhibit preferences for illiberal policies. Furthermore, beyond estimating the overall impact of automation risk, I explore the underlying mechanisms through which such risks shape political behavior, offering empirical evidence for the interplay between economic and cultural factors. My work reveals that exposure to automation triggers feelings of nostalgia and marginalization, ultimately resulting in shifts in political attitudes.

This paper demonstrates the crucial role of cultural grievances in catalyzing reactions to economic shifts, leading to the emergence of the populist backlash (e.g., Ballard-Rosa, Scheve, and Jensen, 2021; Colantone and Stanig, 2018; Green, Hellwig, and Fieldhouse, 2022; Carreras, Irepoglu Carreras, and Bowler, 2019; Hays, Lim, and Spoon, 2019; Baccini and Weymouth, 2021; Gidron and Hall, 2017*a*; Clark, Khoban, and Zucker, 2022). I highlight the interplay between cultural beliefs and technological change, a unique phenomenon creating new losers among the middle class, leading to a hollowing out of this group (Kurer and Palier, 2019; Jaimovich and Siu, 2019). In doing so, I provide an explanation for the emergence of support for the radical right[5]—rather than the radical left—among workers exposed to automation risk. Given the middle class's significant electoral presence,[6] understanding changes in their political behavior (e.g., radicalization or disengagement) is crucial for comprehending shifts in party systems and democratic systems more generally (e.g., Lipset, 1959; Moore, 1966; Boix, 2003; Acemoglu, Acemoglu, and Robinson, 2006).

Empirically, my work offers several significant contributions. Firstly, it employs a novel approach: the double randomization of treatment and mediators, which has not been explored in political science for mechanism analysis before. This approach enhances our understanding of mediation, a critical tool widely utilized in social psychology (Pirlott and MacKinnon, 2016; Bullock and Green, 2021; Spencer, Zanna, and Fong, 2005), shedding light on 'how' and 'why' social effects manifest. By experimentally manipulating both treatment and mediator variables, we can better ensure the independence of mediators from other variables. Secondly, my design introduces a refined compliance approach that accounts for task completion. Finally, this study

[5]This relationship has been previously documented by Im et al. (2019); Frey, Berger, and Chen (2017); Autor et al. (2020)

[6]They represent 25–30 percent of the workforce in advanced capitalist democracies.

breaks new ground as it is the first survey experiment to focus on AI exposure and its impact on white-collar workers, expanding beyond the typical focus on blue-collar workers' risks.

In the remainder of this paper, I first provide a definition of technological change and discuss its relevance. Next, I present the theoretical framework and hypotheses of my study. Subsequently, I outline the merits of an experimental approach and present my design. To bolster the external validity of my findings, I also present an analysis based on observational survey data. This analysis further illuminates how automation risk influences political behavior through cultural grievances.

TECHNOLOGICAL CHANGE AND POLITICS

Automation, characterized as the expansion of tasks that can be performed by capital (Acemoglu and Restrepo, 2018*a*), has dual implications. One form of technological change involves displacement effects, where tasks previously performed by workers are now automated (e.g., Acemoglu and Restrepo, 2019, 2018*a*). The other form involves the creation of new tasks that did not exist before, referred to as reinstatement effects (e.g., Acemoglu and Restrepo, 2019). As a result, automation leads to both winners and losers, generating routine- and capital-biased consequences (e.g., Autor, 2013; Acemoglu and Restrepo, 2018*b*; Dauth et al., 2018; Graetz and Michaels, 2018; Kurer and Gallego, 2019). This job polarization phenomenon manifests as faster wage and employment growth in non-routine occupations, where machines cannot replace human labor (e.g., Autor, Katz, and Kearney, 2006; Goos and Manning, 2007; Goos, Manning, and Salomons, 2009; Autor, 2013, 2015).

Routine occupations mainly refer to middle-skill and middle-wage jobs that are prevalent in blue- and white-collar sectors, such as manufacturing and administration. For example, tax filing software (e.g., Sprintax) can now replace an accountant specializing in taxes, and driverless vehicles can replace truck drivers. High- and middle-level education tasks are not exempt from automation risk either. For instance, in 2017, Google launched a new version of Google Translator using machine learning, which has over 500 million total users and may put human translators at risk of being replaced. More recently, widespread access to AI tools such as ChatGPT or Google Bard has the potential to easily replace tasks performed by research assistants, office clerks, and proofreaders, among others.[7] This affected group of

[7]For instance, a respondent in my survey clearly summarized these concerns about recent changes: "I am a front-end developer and designer. Technology is always evolving in this space, but until recently I hadn't been

workers represents a hollowing out of the middle class, rather than just a decline among poor individuals (e.g., Kurer and Palier, 2019; Jaimovich and Siu, 2019). Recent estimates for the US indicate that workers who are displaced due to technological change lose over 45 percent of their earnings (Braxton and Taska, 2023). These labor market changes and their unequal consequences will likely have multiple political implications.

The political science literature has increasingly focused on voters adversely affected by technological change, linking them to political choices against the status quo (e.g., Frey, Berger, and Chen, 2017; Owen, 2019; Gingrich, 2019; Im et al., 2019; Kurer, 2020; Milner, 2021; Colantone, Ottaviano, and Stanig, 2021; Anelli, Colantone, and Stanig, 2021). However, the mechanisms through which automation influences vote choices have not been firmly established. This study contributes by examining the interplay between automation and cultural grievances, specifically marginalization and nostalgia, and their role in shaping support for populist parties. The following section presents my argument.

A Non-Material Path from Automation to Populism

A recent psychological experiment (Granulo, Fuchs, and Puntoni, 2019) shows that when job losses affect others, individuals prefer human workers to be replaced by other human workers rather than robots. However, when facing their own job loss, individuals prefer to be replaced by robots. These puzzling results suggest that a possible explanation for the changes in behavior is status threat. If a human replaces "you," it implies someone else is taking "your job" and performing better than you. Other studies also highlight non-economic consequences of exposure to automation risk, such as reduced marriage rates, increased divorces, reduced fertility, and an increase in working-mortality due to feelings of despair (Anelli, Giuntella, and Stella, 2021; O'Brien, Bair, and Venkataramani, 2022). My work builds on these insights to propose a cultural pathway for understanding the link between technological change and political behavior.

I examine how exposure to automation risk may influence political behavior by making exposed citizens more likely to hold populist preferences, and in particular to support populist right parties. The central argument is that the threat of job loss can evoke cultural grievances, thereby influencing individuals' political responses. As suggested by previous scholars, populist

worried about it. I just kept learning the new languages and frameworks. Then ChatGPT came out and can write all sorts of code. It wasn't until this that I started to worry."

right candidates serve as a representation channel for individuals with cultural grievances arising from a fear of social change. Individuals' job conditions significantly impact their feelings of insecurity or stability, aligning with Inglehart (2018)'s assertion that "economic and physical insecurity are conducive to xenophobia, strong ingroup solidarity, authoritarian politics, and rigid adherence to their group's traditional cultural norms" (p.8). In particular, "status anxiety" is posited to play a key role in vote choice decisions (Kurer, 2020; Gidron and Hall, 2017*b*).

Economic crises create fertile ground for the emergence of anti-establishment politics that amplify cultural grievances, including feelings of marginalization (e.g., resentment towards outgroups) and a longing for a bygone era characterized by different societal structures. In this paper, I propose a theory that asserts that changes in long-term economic structures, such as job automation, not only directly impact political behavior but also give rise to a sense of dissatisfaction. This dissatisfaction manifests as a perception of marginalization, encompassing feelings of mistreatment and lack of recognition within society, also leading to a strengthened attachment to an idealized past. Consequently, these shifts in symbolic attitudes influence anti-elite populist sentiments and trigger other illiberal policy preferences. The diagram presented below illustrates the non-material-cultural pathway from automation to radical right populism. I propose two distinct paths through which this occurs: marginalization and nostalgia. In this section, I outline and describe these paths, drawing on relevant theories from psychology and voting behavior research.

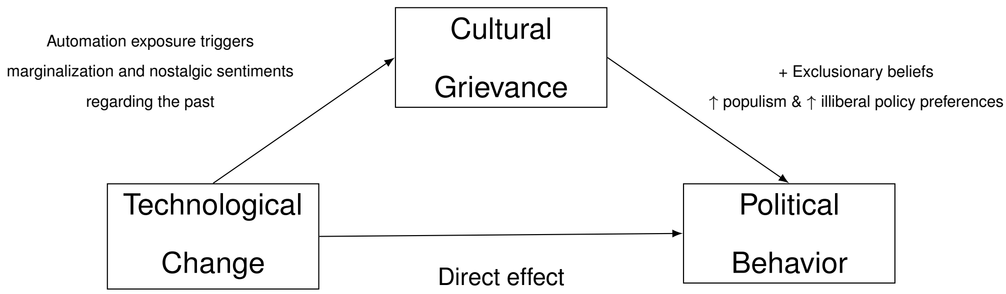

Figure 1: Mediator causality DAG

Marginalization

Most theories attempting to understand the rise of populism or globalization backlash typically focus on either cultural grievances or economic decline but fail to recognize the interconnected nature of these phenomena. Particularly, when considering significant shifts in the economic structure, such as long-term job displacement resulting from automation, it is plausible to assume that workers who harbor concerns about their job prospects and overall ability to sustain themselves in the coming months or years may feel that they are being left behind. Based on my survey responses, several illustrative comments support this notion. One respondent asserted, "The fear of not being able to survive is the problem, not the tech," making a strong statement that extends beyond a mere threat to one's status—it touches on matters of life and death. Another respondent emphasized, "We MUST think about the REAL PEOPLE behind these jobs who would be pushed out of the workforce. Technology is for our use, not for it to use us" (emphasis from the respondent). The focus on "real people" and the expression of being "pushed out" serve as a plea to prioritize the well-being of those who are neglected, marginalized, pushed to the periphery, and likely on the verge of societal exclusion.

Previous studies on British and American workers have suggested that white working-class individuals may perceive themselves as marginalized in society when faced with the threat of economic decline (Gest, Reny, and Mayer, 2018). Similarly, Ballard-Rosa, Goldstein, and Rudra (2023) finds that "economically anxious" meritocrats, who are concerned about their prospects for upward mobility, are more inclined to adopt anti-trade views when influenced by certain elite stimuli. This sense of being "left behind" is not only accompanied by tangible material consequences resulting from job automation, but also entails a perceived lack of recognition and respect for their social group within society. Such discontent and feelings of alienation can contribute to their disengagement from mainstream political discourses and, in turn, foster support for radical populist parties.

In addition to the individual and collective perception of being undervalued within society, frustrations can manifest as a sense of entitlement and a belief in deserving more recognition compared to other groups. This discontent has the potential to lead to the expression of prejudices towards outgroups. Theories explaining attitudes toward outgroups have shown that individuals experiencing discomfort and threat may attribute blame to social outgroups (Allport, 1954; Glick, 2005). This mechanism helps them to restore a sense of personal control (Bukowski et al., 2017). Technological change, in particular the incorporation of robots into the workplace, can increase exposure to risks and fears of losing one's job. Figure A.2 in the appendix shows that workers facing higher automation risk are more likely to have concerns about losing jobs, to have fears about difficulties in finding a new job, to experience job insecurity, and to be unsatisfied with their work. As experimentally demonstrated by Granulo, Fuchs, and Puntoni (2019), fear about subjects' work may depress prosocial feelings, triggering social comparison.

Past work has extensively documented that economic threat associated with economic decline, natural disasters, and unemployment generates outgroup hostility (e.g, Andrighetto et al., 2016; Brambilla and Butz, 2013; Gamez-Djokic and Waytz, 2020; Hepworth and West, 1988; Hovland and Sears, 1970). When people face scarcity, such as job scarcity, self-perceptions about one's worth and others' worth may change, generating more pro-discriminatory behavior as justification for preferences to withhold scarce resources (Krosch and Amodio, 2014). In particular, individuals from economically depressed regions (Hernes and Knudsen, 1992), low-skilled individuals (Scheve and Slaughter, 2001), or those from shrinking sectors (Dancygier and Donnelly, 2013) can perceive immigrants as a threat to their jobs and can develop anti-immigrant attitudes.

Building on the growing scholarship examining automation and attitudes toward immigration (Kaihovaara and Im, 2020; Gamez-Djokic and Waytz, 2020; Wu, 2022*a*), I expand our understanding of how exposure to job automation may trigger feelings of marginalization affecting individuals' political behavior. Unlike previous assumptions of blame misattribution or voter ignorance (Wu, 2022*a*; Mansfield and Mutz, 2013), I argue that automation triggers feelings of marginalization, which account for reactions towards minority groups, even in contexts such as my experiment, where information and rationales for displacement are explicitly provided. Despite the provision of such information, individuals still experience heightened feelings of marginalization and hostility toward immigrants. The discontent stemming from heightened automation risk aligns with populist rhetoric, which targets those who have been overlooked or excluded by corrupt elites. Consequently, my work completes the cycle connecting automation to political behavior.

Nostalgia

Technological change plays a pivotal role in reshaping employment relationships within post-industrial societies (Anelli, Colantone, and Stanig, 2021). These profound transformations have the potential to challenge established ways of life and societal values. As an example, even middle-class workers who may have previously been unaffected by other economic shocks, such as globalization, are now grappling with the fear of being replaced by machines. During periods of significant social change, individuals may experience nostalgic sentiments that yearn for a secure and familiar past, which serve as a comfort-seeking mechanism (Brown, Kozinets, and Sherry, 2003).

Research on the origins of nostalgia has linked it to feelings of discontent, anxiety, fear, and overall dissatisfaction with one's current life (Davis, 1979; Hirsch, 1992). During times of anxiety, like economic recessions, individuals tend to seek nostalgic feelings as a means to alleviate uncertainty (Elliot, 2009; Barauskaitė, Gineikienė, and Fennis, 2022). For example, Barauskaitė, Gineikienė, and Fennis (2022) explore the concept of being "saved by the past" and how the threat of the Covid-19 pandemic triggered nostalgic consumption.

Prior research has found that the sentimental longing for the past, often idealized as a golden era, frequently implies an angle for a restrictive past, which predominantly favored certain demographics, such as white males from the mining industries (Kojola, 2019). In a similar vein, a recent study by Clark, Khoban, and Zucker (2022) suggests that as primary earning roles for men decline, coalitions nostalgic for bygone patriarchal eras may emerge, thereby bolstering more conservative candidates.

The potential consequences of automation and the fear of job loss can generate personal insecurities, such as concerns about job stability and societal anxiety regarding the vulnerability of others. Past research suggests that nostalgia consumption effectively alleviates insecurities by providing a sense of familiarity and stability (Hart, Shaver, and Goldenberg, 2005; Rindfleisch, Burroughs, and Wong, 2009). It acts as a psychological salve for threatening experiences (Sedikides, Wildschut, and Baden, 2004).

This yearning for safety and desire to restore past hierarchies aligns with populist right rhetoric, which evokes bittersweet feelings about the past (van Prooijen et al., 2022; Mutz, 2018). Previous studies have linked feelings of nostalgic deprivation and societal pessimism to support for radical right-wing ideologies (e.g., Steenvoorden and Harteveld, 2018; Gest, Reny, and Mayer, 2018; de Vries and Hoffmann, 2018). Building on these works, it is reasonable to suggest that individuals exposed to automation risk may develop nostalgic sentiments and a desire for nostalgic consumption.

When Populism Meets Discontent

Contemporary populist rhetoric effectively appeals to individuals who perceive themselves as threatened by socioeconomic transformations. For example, during his presidential campaign, Donald Trump's rhetoric resonated with workers who felt neglected, referring to them as the "forgotten workers."[8] Similarly, Giorgia Meloni's recent electoral success as the leader of the

[8] Rally in Dimondale, August 2016.

populist radical right Brothers of Italy party exemplifies the use of ingroup versus outgroup appeals. Meloni prioritized the interests of Italian citizens over foreigners, explicitly opposing mass immigration and emphasizing work for the people.[9] She formed a coalition with the right-wing populist League party, led by Matteo Salvini, known for employing xenophobic language attributing employment issues to immigrants. Salvini contrasted the difficulties faced by vulnerable natives with the arrival of immigrants, creating a perceived distinction between deserving natives and undeserving migrants, appealing to individuals who feel marginalized and disenfranchised by mainstream political parties (Mcginnis, 2021).

Nostalgia also plays a significant role in the realm of populist rhetoric. Politicians often engage in the romanticization of past economic and cultural norms to garner support, as demonstrated by leaders like Donald Trump with his iconic slogan "make America great again," and Boris Johnson, who evoked a sense of Britain's former power. This nostalgic appeal was particularly evident in slogans used during the Brexit referendum, such as "let's take back control," "BeLeave in Britain again," and "we want our country back."[10] These slogans all revolve around an idealized past, seeking to strengthen social bonds among those who long for these bygone times. In this idealized era, there was likely a sense of order, job stability, and a reduced risk to the middle class.

In summary, this paper contributes to the literature by emphasizing the endogenous nature of cultural dispositions, feelings of marginalization, and nostalgia as responses to economic threats, particularly automation risk. The ongoing automation wave is likely to generate structural changes, triggering individuals' personal and societal insecurities, which in turn can influence their voting choices. Based on this framework, the following testable hypotheses are proposed:

Hypothesis 1. ***Populism and Illiberal Policies****: Individuals who are exposed to automation risk are more likely to develop populist attitudes and illiberal policy preferences.*

Hypothesis 2. ***Cultural Grievance****: Individuals who are exposed to automation risk are more likely to experience a sense of marginalization and nostalgia.*

Finally, I hypothesize that cultural grievances mediate part of the effects of automation risk on individuals' vote choices:

[9] See, for example, speech on June 13, 2022 (source: YouTube).

[10] See more examples in The Brexit collection, LSE Digital Library.

Hypothesis 3. ***Mediated Effect****: The effect of exposure to automation risk on support for populist parties and illiberal policy preferences is mediated by feelings of discontent related to marginalization and nostalgic sentiments.*

TESTING THE AUTOMATION PATHWAY: MEASURES, METHODS, AND RESULTS

In this section, I empirically evaluate my hypotheses using both experimental and observational data. My conceptual framework concerning political behavior focuses on the mediating role of exposure to automation risk, which elicits perceptions of marginalization and fosters nostalgia for a better past. Subsequently, these sentiments contribute to the rise of populism, particularly anti-elitism, and engender illiberal attitudes. If my theory holds, it suggests that technological advancements serve as the underlying catalyst for this effect. Consequently, this effect remains obscured in analyses that solely consider the economic dimension, as it also engenders changes in symbolic preferences (nostalgia and marginalization).

It is important to note that this approach does not exclude the possibility that cultural threats also contribute to the surge of populism. However, my theory posits that these phenomena, encompassing both economic and cultural changes, are mutually reinforcing. In conclusion, the key implication of my findings is that individuals may develop an augmented perception of marginalization, both in terms of their values and personal identity, as well as a nostalgic belief that the past was superior, when confronted with economic threats of job loss from technological change.

STUDY 1: EXPERIMENTAL EVIDENCE

Survey experiments present exceptional advantages when examining the impact of economic threats on individuals' attitudes and their inclination toward supporting populism. Through the random assignment of crucial explanatory variables, such as exposure to job displacement caused by automation, the issues of endogeneity and spurious correlation can be circumvented. Experimental designs also provide safeguards against omitted variable bias by independently manipulating factors that would otherwise co-occur in observational data. Finally, by measuring how a subject's exposure to risks affects perceptions of fear, anxiety, nostalgia, and marginalization, my experiment offers distinct strengths in elucidating the causal pathways under investigation.

Past Experimental Approaches to Automation and Novelty of the Design

To date, only a limited number of studies have utilized survey experiments to explore the effects of job automation on individuals' attitudes. Wu (2022*b*) conducted a survey experiment comparing various sources of job threats. Her findings indicate a modest increase in support among Democrats for restricting technological integration. Additionally, Mutz (2021) observes a decline in support for international trade when individuals were exposed to job loss resulting from automation. Furthermore, in the field of psychology, Yam et al. (2022) demonstrate that employees who experienced exposure to robots, either physically or psychologically, reported heightened job insecurity. Likewise, Granulo, Fuchs, and Puntoni (2019) documented a decrease in pro-social sentiments when participants evaluated their own job prospects, expressing a preference for being replaced by a robot rather than a human.

These aforementioned studies, while showcasing innovation, are subject to several critiques. First, previous studies in political science have primarily emphasized comparisons of various sources of threat rather than concentrating on the direct consequences of job replacement by technology itself. This limitation hampers the ability to attribute the observed effects specifically to the adverse impact of technology. Second, all prior research has predominantly focused on exposing participants to technological changes manifested as manufacturing job losses, such as plant closures. However, it is essential to acknowledge that technological advancements also impact middle-class and middle-skill workers, particularly with the incorporation of AI into the workplace. Third, existing studies have not explored political outcomes such as anti-elitism or individuals' attitudes, including feelings of marginalization and nostalgia. Fourth, previous surveys merely prompt subjects with different news articles, with no further framing that questions the validity of ecological inference, and assuming a passive role for respondents.

Finally, although prior studies have presented evidence indicating that exposure to job automation increases the inclination to support trade restrictions and slightly increases support for limiting the use of robots, they have not thoroughly investigated the fundamental underlying mechanisms driving this pattern. Exposure to automation risk could potentially foster a willingness to endorse illiberal policies and harbor populist attitudes for various reasons, yet previous studies were not explicitly designed to answer how and why these phenomena relate. In my research, I build upon previous experiments in several significant ways. First, I conducted a survey that compares technology in a neutral context with technology resulting in job losses, while also ensuring larger sample sizes. Second, I implemented variations to the treatment to analyze the effect of the incorporation of robots, predominantly affecting blue-collar workers, or the integration of AI, primarily impacting white-collar workers. This approach sheds new light on the impact of the recent irruption of AI. Third, I incorporated additional political outcomes of interest to gain a comprehensive understanding of the consequences stemming from exposure to automation risk. Fourth, I implemented active participation tasks and created an ecologically valid news consumption experience within the experiment. Lastly, I designed my experiment not only to examine the presence or absence of changes in political behavior resulting from exposure to automation risk but also to shed light on the mechanisms behind these changes.

Experimental Design and Procedures

I fielded the survey in the United States using the CloudResearch-Mturk toolkit between May 23 and May 29, 2023, collecting 3133 responses from US citizens, 18 years or older, who were part of the workforce (currently working or looking for a job).[11,12] I implemented a design-based experimental mediation analysis with double randomization of the treatment (exposure to automation risk) and encouragement of mediators (marginalization and nostalgia).[13] In the first study, the treatment (exposure to automation risk) is randomly assigned, generating a pure treatment and pure control group, but no manipulation of mediators (marginalization and nostalgia) is conducted. In the other study, I randomized the treatment (automation), splitting the sample into treatment and control groups. Then, each group was randomly assigned to a marginalization or nostalgia mediator encouragement.

I adopted and modified the tasks for respondents based on studies conducted by Lelkes and Westwood (2017) and Amira, Wright, and Goya-Tocchetto (2021). In this task, respondents were presented with two news articles and given the responsibility of comparing and evaluating them to assist a startup online news content platform in deciding which article to publish. This approach aims to provide an ecologically valid news consumption experience. In the treatment condition, participants were exposed to two news articles discussing job displacement caused

[11] I registered the study after running a pilot with Open Science Framework (OSF). The process of data collection started after registration.

[12] I implemented several measures to ensure data quality, including CAPTCHA to prevent spam and bots, location screening to limit participation to the United States, attention checks, manipulation checks, survey timekeeping, a minimum time for some sections, and a minimum number of characters in writing exercises. To be considered for the analysis, respondents had to have a 90 percent survey approval HITS on CloudResearch and pass two attention check questions.

[13] For further reference of this method see Imai, Tingley, and Yamamoto (2013); Spencer, Zanna, and Fong (2005); Pirlott and MacKinnon (2016).

by automation, focusing on either manufacturing jobs or white-collar jobs affected by artificial intelligence. In contrast, the control condition featured two news articles related to technological advancements in a more neutral context. The treatment involved providing participants with informative newspaper articles, resembling content that can be found in publications such as the *New York Times*. One article highlighted an individual who recently lost their job as a result of technology incorporation, serving as a single identifiable victim, while the other article addressed the broader issue of upcoming layoffs and the overall impact on a collective group or community affected by technological change. In both the treatment and control conditions, two sets of news articles focusing on the same topic were provided. The following was the cover story used:

> The researchers hosting this survey are conducting it for the founders of an online news website about social change that launched about 3 months ago. In this short time period, their website has seen far more traffic than originally expected. Since their company is new to the online marketplace, they are conducting research on the topics and stories that consumers think are the most important. While most of the content appearing on their website homepage is selected by the editors, they have reserved certain slots for posts that the public can vote on. We would like your input regarding which of the following two articles should appear on next week's homepage.

For the second group, in which mediators are manipulated, the treatment and control were the same as the ones described above. Then, to encourage feelings of nostalgia or marginalization discontent, subjects were asked to do a short writing exercise (autobiographical emotional memory task). The framing of this exercise was that the news organization is deciding whether to add a new section called "letter to the editors" which includes short passages from readers. Participants were prompted to think about a time in their life that made them feel a particular emotion. Those assigned to nostalgia saw a prompt that defines nostalgia, while those assigned to marginalization saw a prompt asking them to write about a time they felt intimidated by people different than them. The prompt explicitly asked subjects to "think of all the details of what was happening at the time, to the point that you could imagine this is happening to you now. Think about when this happened, who was involved, and what your feelings were." They were asked to spend 90 seconds on this task and to add enough detail so that someone reading their story could feel what they felt. I designed this task to encourage emotions from respondents, based on previous work in social psychology and political science.[14]

After completing these tasks (reading and writing), participants were asked if they would endorse the article for inclusion on the online news platform organization's and support the proposed new section. This design allows respondents to focus on the text and provides a more natural news consumption experience. Moreover, following the news tasks, respondents were asked to describe their feelings after reading these articles with 5 options: anger, fear, uneasiness, enthusiasm, and none of the above.[15]

In the post-treatment section of the survey, I asked about respondents' political attitudes, public policy preferences, subjective exposure to risk, and cultural grievances, as I am primarily interested in investigating changes in political behavior. Specifically, I aim to assess whether the automation of jobs influences political behavior such as levels of populism, voting behavior, and policy preferences, as well as cultural attitudes, including nostalgia or discontent related to marginalization. The political behavior questions encompassed various topics, such as support for a potential Trump candidacy in the 2024 presidential election, evaluations of whether trade benefits American workers (core elements of neo-mercantilist foreign economic policies), preferences for taxing the wealthy, and other policies commonly associated with populist leaders worldwide.

My measure of populist attitudes follows recent debates on the conceptualization of populism anchored in the work of Mudde (2004), who states: "populism, first and foremost, [is] a set of ideas focused on a fundamental opposition between the people and the elite." This definition includes pro-people attitudes ("us"), negative judgments of the 'elite' who are considered "them," and Manicheism. I relied on previously used survey questions (refer to Castanho Silva et al., 2018; Rhodes-Purdy, Navarre, and Utych, 2021). For example, to proxy populism as anti-elitism, I asked respondents to what degree they agree with the following statement: "The government is pretty much run by a few big interests looking out for themselves."

Shifting attention to the mediators, I employed various questions previously utilized in psychology studies to measure nostalgic feelings. To capture individual-level perceptions of nostalgia, respondents were asked to what extent they felt sentimental for the past (Newman

[14] See examples such as Xia, Wang, and Santana (2021), van Tilburg, Sedikides, and Wildschut (2015), Newman et al. (2020). Moreover, similar task-writing approaches were recently used in political science works such as Rhodes-Purdy, Navarre, and Utych (2021) and Busby, Gubler, and Hawkins (2019).

[15] Almost all respondents picked one of these emotions.

et al., 2020). Additionally, questions related to collective nostalgia were included, such as whether many American traditions have been lost over time or if American identity is no longer what it used to be in the past (e.g, Smeekes, Sedikides, and Wildschut, 2023; Smeekes, Verkuyten, and Martinovic, 2015). Respondents indicated their level of agreement with these statements, allowing for the creation of an index representing nostalgic feelings.

To assess feelings of marginalization, I examined individual-level perceptions of disrespect for the individual's own values, poor treatment in society, and collective perceptions of adversity faced by people similar to them in society.[16]

Finally, to serve as manipulation checks and to gain insight into the subjective perception of risk, I included several questions toward the end of the survey that aimed to assess respondents' concerns about the possibility of losing their current job due to automation, their outlook on future job prospects, and their general evaluations of the future of work in society.

To assuage concerns that convenience samples may not yield results representative of the entire population, I have included summary statistics in the Appendix B.2 and their correlations with national survey samples. The sample aligns closely with the target population in terms of ethnicity, gender, and age.

Estimation Strategy

Survey experiments often establish a treatment-outcome relationship without exploring the underlying mechanisms, commonly referred to as the 'black box' of causality (Spencer, Zanna, and Fong, 2005; Brady and Collier, 2010; Imai et al., 2011). In response to this gap, mediation analysis has become a valuable tool, particularly in social psychology (Pirlott and MacKinnon, 2016).[17] Mediation analysis clarifies 'how or why' social effects occur, offering comprehensive insights for behavior prediction and policy intervention reconsideration (Baron and Kenny, 1986).

Causal mechanism establishment hinges on identifying a mediator bridging treatment and outcomes. Baron and Kenny (1986) introduced a foundational framework utilizing a multi-equation regression approach. It posits that the effect of an intervention (e.g., exposure

[16]Specifically, respondents were asked to indicate their degree of agreement with statements such as "My values are not respected in this country," "People with values like mine are treated poorly in this society," and "Regardless of who is in political power, things are generally pretty bad for people like me." These questions were previously used by Rhodes-Purdy, Navarre, and Utych (2021).

[17]Editors at top social psychology journals like the Journal of Experimental Social Psychology and the Journal of Personality and Social Psychology (JPSP) emphasize the need to establish causality and elucidate mechanisms. This is reflected in the widespread adoption of this method in journals such as JPSP and Personality and Social Psychology Bulletin (PSPB), with 59% and 65% of articles, respectively, from 2005 to 2009 (Pirlott and MacKinnon, 2016). This trend continues, with 55 papers in JPSP using this method in 2019.

to automation risk, X) on an outcome (e.g., political behavior, Y) is mediated through an intermediary (M). They propose a structural equation model (equations 1-3), with index i denoting subjects, α represents intercepts, and ϵ signifies zero-mean error terms reflecting unobservable variables' impact. The total effect of X on Y is denoted as c, while the direct effect is d. The mediated effect can be estimated using either the product-of-coefficients method (ab) or the difference ($c - d$). The proportion of the treatment effect explained by each mediator is the indirect effect divided by the total treatment effect. This study argues that cultural grievances, expressed as nostalgia and marginalization, serve as this mediating mechanism.

$$M_i = \alpha_1 + aX_i + \epsilon_{i1} \tag{1}$$

$$Y_i = \alpha_2 + cX_i + \epsilon_{i2} \tag{2}$$

$$Y_i = \alpha_3 + dX_i + bM_i + \epsilon_{i3} \tag{3}$$

The common approach to mediation analysis, known as *measurement-of-mediation* or model-based, involves measuring mediator changes using equation 1 (Spencer, Zanna, and Fong, 2005). Despite its prevalence, this method may encounter assumptions violations, such as a likely relationship between error terms ϵ_1 and ϵ_3, potentially due to unobserved confounders between M and Y (Spencer, Zanna, and Fong, 2005; Imai and Yamamoto, 2010; Bullock and Green, 2021; Bullock, Green, and Ha, 2010). A common misconception suggests that randomizing the independent variable can mitigate biases in mediation analysis (Bullock, Green, and Ha, 2010). However, while randomizing X ensures no systematic relationship with ϵ_1 or ϵ_3, it does not guarantee that M or Y are not systematically linked to these error terms, potentially introducing bias.[18]

In my *design-based experimental analysis*, I address this issue by experimentally manipulating both the treatment and the mediator, thereby facilitating unbiased estimations of b, and ensuring temporal precedence from X to M and M to Y (Pirlott and MacKinnon, 2016; Bullock, Green, and Ha, 2010). I employ causal mediation analysis to decompose the average treatment effect (ATE) or total effect (equation 2) into two distinct components: the average causal mediated effect (ACME), arising from the product of coefficients between X and M and M and Y, and the average direct effect (ADE), representing the remaining effect.

[18]Measurement-of-mediation analysis design has been applied in top political science journals, including works based solely on observational data such as Karpowitz, Mendelberg, and Shaker (2012), Hays, Lim, and Spoon (2019), and Frymer and Grumbach (2021), as well as studies involving randomized treatment assignment in Tomz and Weeks (2013), Tomz and Weeks (2020), Powers and Renshon (2023), Young (2019), Schwartz et al. (2021), and Wolak (2020).

I begin my analysis by estimating the total effect (equation 2), derived from the expected outcome differences between treatment and control conditions. I perform regressions for each outcome of interest (populism and indicators of illiberal policy preferences) against the treatments. This analysis is also replicated by combining the robot and AI treatments.

Subsequently, I extend the analysis by regressing the mediator, cultural grievances, across its dimensions (nostalgia and marginalization) with respect to the treatments. This establishes the relationship between exposure to automation risk and the mediators (equation 1).

To test the mediated aspects of my theory, I must estimate the impact of encouraging the mediator on political attitudes. This task is not without challenges. The first assumption I must invoke is that the experimental encouragement of mediators exclusively impacts that specific mediator and not others (Bullock, Green, and Ha, 2010). In my case, I relied on previous work in social psychology to design the encouragement of the mediators, which I do via reflective tasks on the topics (e.g., Xia, Wang, and Santana, 2021; van Tilburg, Sedikides, and Wildschut, 2015; Newman et al., 2020; Bhattacharya, 2020). My initial approach involves estimating the relationship between M and Y through matching based on pre-treatment covariates.

However, a second challenge emerges as the encouragement may not impact the entire sample (Bullock, Green, and Ha, 2010; Pirlott and MacKinnon, 2016). Addressing this challenge requires accounting for non-compliers due to potential biases that may arise when recipients of the encouragement deviate from the initial assignment (Angrist, Imbens, and Rubin, 1996; Balke and Pearl, 1997). Compliers are individuals for whom the value of M changes in the expected direction upon receiving encouragement.

To address this challenge, my first attempt follows Balke and Pearl (1997), who proposed non-parametric solutions known as sharp bounds. However, these bounds proved uninformative, and to narrow them down, a set of additional assumptions for this case would be needed (Imai et al., 2011; Blackwell et al., 2023; Knox, Lowe, and Mummolo, 2020). Hence, I implement an alternative solution by adopting the intent-to-treat (ITT) approach (Angrist, Imbens, and Rubin, 1996) and enhancing it by incorporating a detailed compliance measurement that I formulated, given that my encouragement took the form of a task. I assessed this by observing task completion intensity, evaluated by the extent of content covered. By adopting this strategy, we can better estimate the encouragement's effects, reducing biases associated with imperfect compliance and establishing a metric that considers high mediator levels and task completion.

Treatment (and encouragement) effect heterogeneity can undermine the validity of the product-of-coefficients approach to estimating the mediated causal effect (Bullock, Green, and Ha, 2010; Imai et al., 2011; Pirlott and MacKinnon, 2016). Essentially, this heterogeneity means that the effects of X on M and M on Y do not remain consistent across all participants. Imai et al. (2011) proposes a solution that encourages low and high mediator levels and employs non-parametric bounds. However, this approach does not provide point estimates but rather offers bounds, which are often uninformative (Bullock and Green, 2021), and require various levels for the mediator.[19]

To place trust in the results of the design-based experimental approach, one might consider adopting an assumption used in prior mediation studies: "monotonicity" (Bullock and Green, 2021; Knox, Lowe, and Mummolo, 2020). This assumption implies that treatments (and encouragement) consistently have either a nonnegative or nonpositive effect (i.e., there is no sign heterogeneity). In simpler terms, for all subjects i, either $M_i(1) \geq M_i(0)$ or $M_i(0) \leq M_i(1)$. However, it's crucial to acknowledge that researchers cannot empirically test this assumption. As Bullock and Green (2021) notes, "One must construct arguments grounded in theory to support them" (p.9).

This assumption of monotonicity implies that subjects facing the risk of automation would feel heightened nostalgia and a stronger sense of exclusion. The opposite response should not happen: exposure to the treatment should not result in lessened cultural grievances compared to the control group. Similarly, subjects encouraged with respect to the mediators (nostalgia and marginalization) should not exhibit less support for the populist right.

Based on these assumptions, once I estimate the relationships between X and M, as well as M and Y, I calculate the indirect effect using the product-of-coefficients. Additionally, I compute confidence intervals for the indirect effect estimates following Sobel (1982), which rely on the Delta method (see Appendix C.5 for further explanations).

Finally, I replicate the analysis as a measurement-of-mediation analysis using the observed values of M. This complements the manipulation-of-mediation analysis, and the convergence of results offers valuable insights into a mediation relationship, addressing concerns that encouraged mediators inherently become moderators (Pirlott and MacKinnon, 2016). The following sections present the results for each of these estimations.

[19] In empirical simulations replicating Imai et al. (2011), these bounds were found to lack informativeness in some scenarios, and optimization was infeasible under certain random seeds.

Evidence for the total effect of Exposure to Automation Risk on Politics

The summary of the overall effect of exposure to automation on various political outcomes is presented in Figure 2, and is largely consistent with my theoretical expectations. The comparison is between individuals who read news articles specifically related to job automation and those who read neutral articles on technological development. Additionally, the plot illustrates the differentiated average treatment effects when the news pertained to robots affecting manufacturing industries or to the incorporation of artificial intelligence impacting white-collar workers. All estimates include pre-treatment control variables, such as gender, race, occupation (using the routine task intensity index), income, and education levels.

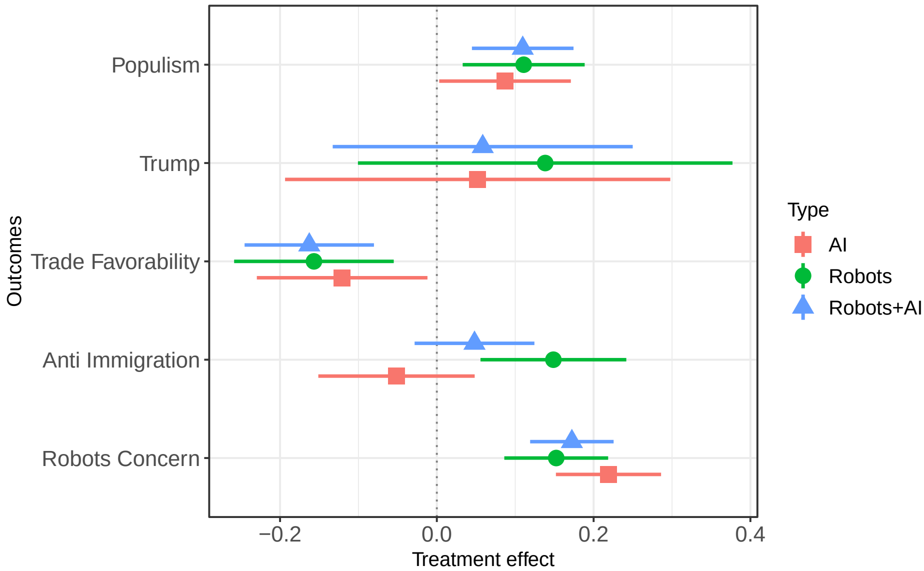

Figure 2: Total Effect of Exposure to Automation Risk (proxied as robots and AI).
Note: All variables, with the exception of 'Trump' (coded as 0 or 1), have been converted to a 1-5 point scale.

As shown in Figure 2, individuals exposed to automation risk were more likely to hold populist attitudes. For instance, on average, respondents in the treatment group scored 0.113 higher on the 5-point populism (anti-elitism) scale variable. Regarding specific support for Trump, the estimate is positive, but there is not enough evidence to reject the null hypothesis of no relationship. The estimates also indicate an increase in illiberal attitudes, such as worse evaluations of trade as good for American workers, which aligns with previous findings documenting an increase in demands for tariffs (Mutz, 2021; Wu, 2022*b*). Overall these results provide support for **Hypothesis 1**, which posits a connection between exposure to risk and political attitudes.

Regarding the different treatment conditions, the Robot condition exhibited a significant influence on all expected outcomes and mediators. On the other hand, the AI condition provided support for most outcomes (excluding anti-immigration), but the magnitude of these effects appeared weaker compared to when participants were exposed to news about robots. A potential explanation for the weaker effects of the AI treatment could be that workers still perceive AI displacement as improbable, while acknowledging the possibility of displacement caused by robots.

Another noteworthy result from this figure is that exposure to news about job automation consistently generated an increase in automation concerns, confirming the effectiveness of the treatment. Additionally, when examining the negative emotions evoked by the treatment (uneasiness, anger, and fear), I observed a statistically significant difference between the treatment and control groups. For instance, the probability of individuals in the treatment group indicating that they felt enthusiastic about technological change was only 6.4 percent, whereas in the control condition, it was approximately 77.5 percent.

In short, my study provides experimental evidence supporting the connection between exposure to news about automation risk and various political behaviors and attitudes.

Evidence for the effect of Exposure to Automation Risk on Mediators

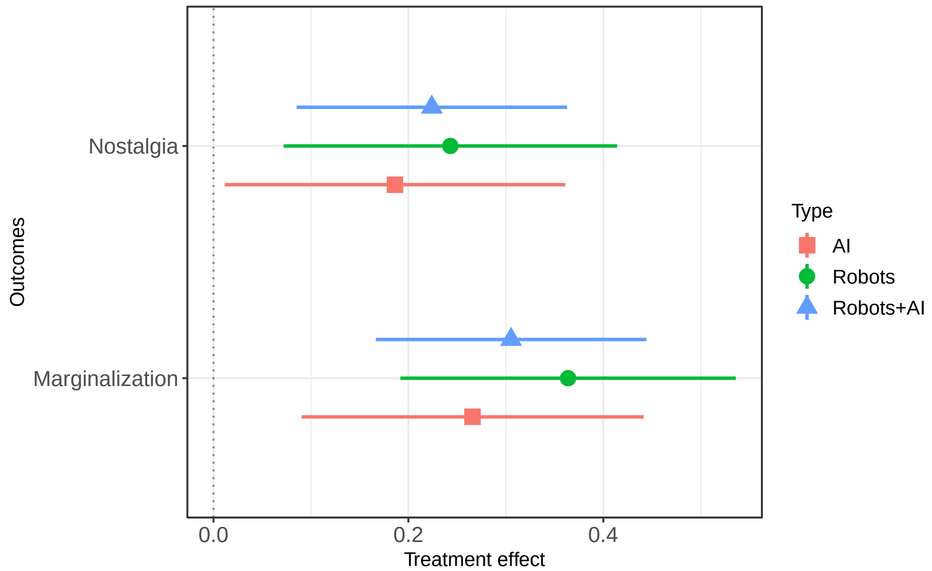

Figure 3: Treatment Effects of Exposure to Automation Risk on mediators.

Note: High values on dummy variables represent 'nostalgia' and 'marginalization' for scores above the median.

Moving on to **Hypothesis 2**, exposure to automation risk increased the likelihood of scoring high on the feelings of marginalization, resulting in a change of about 36 percentage points (see Figure 3). Moreover, exposure to news about technology-induced job loss had a significant impact on high levels of nostalgia, around 24 percentage points.[20]

In conclusion, this economic phenomenon not only impacts preferences such as trade restrictions (as evident in the least favorable evaluations of trade's consequences on American workers) but also generates changes in cultural grievances in line with Hypothesis 2.

Evidence for Causal Mechanisms

As demonstrated earlier, exposure to news stories about job-threatening technological change triggers cultural grievances, which I argue are essential mediators in the relationship between the treatment variable (exposure to automation) and the final outcomes (populist attitudes, support for Trump, and opposition to trade, among others). To unpack this causal mechanism, I conducted an experiment in which I randomized the encouragement of these mediators. However, the design only allows for the encouragement of mediators rather than directly assigning these feelings to respondents, which presents a challenge regarding compliance.[21]

I estimate the causal mediation effect in the following steps. First, I estimate the effect of mediator encouragement on political attitudes using matching. Next, to address the possibility of endogenous compliance, I implement an intent-to-treat (ITT) analysis using random assignment as an instrumental variable.[22] Finally, I conduct a causal mediation analysis, utilizing model-based inference and the observed mediator values.

The estimated encouragement effects using matching are presented in Figure 4. The mediator seems to have no effect on populism, but the encouragement does increase support for Trump, a specific pathway connecting the treatment to Trump that is obscured in the total effect estimate. Notably, the share of respondents supporting Trump increased by approximately 3 percentage points among those who were randomly assigned to the encouragement. This sheds some light on a potential pathway linking automation to cultural grievances and, ultimately, support for Trump.

[20] Figure C.5 presents the estimated effect of the index comprising all questions related to nostalgia and marginalization.

[21] Refer to Imai, Tingley, and Yamamoto (2013) for further discussion.

[22] I also employ nonparametric bounds, but the resulting bounds are uninformative without the addition of substantive assumptions to the causal structure. The discussion of bounds is in Appendix C.4 (see also Figure C.13).

In Figure 4, the estimated intervals exhibit a general increase in illiberal policy preferences. The average effects of the encouragement on trade and immigration are statistically significant. The share of respondents who view trade and immigration favorably drops by 1 and 2.5 percentage points, respectively, for those randomly assigned to the encouragement. The average effects of the encouragement appear to be relatively modest. This could be explained by noncompliance with the encouragement. Therefore, I estimate the average encouragement effect for compliers. Since compliance could be endogenous, I instrument for compliance using random assignment to the encouragement. I define compliers as those with high levels of the mediators (more than the median in the sample)[23] who completed the task (characterized by writing more words than the median).[24] Figure 5 presents results that are consistent with the estimated effects of random assignment to the encouragement, except the magnitude of the effects are larger. Among the compliers, the share who view trade and immigration favorably drops by 26 and 25 percentage points respectively.

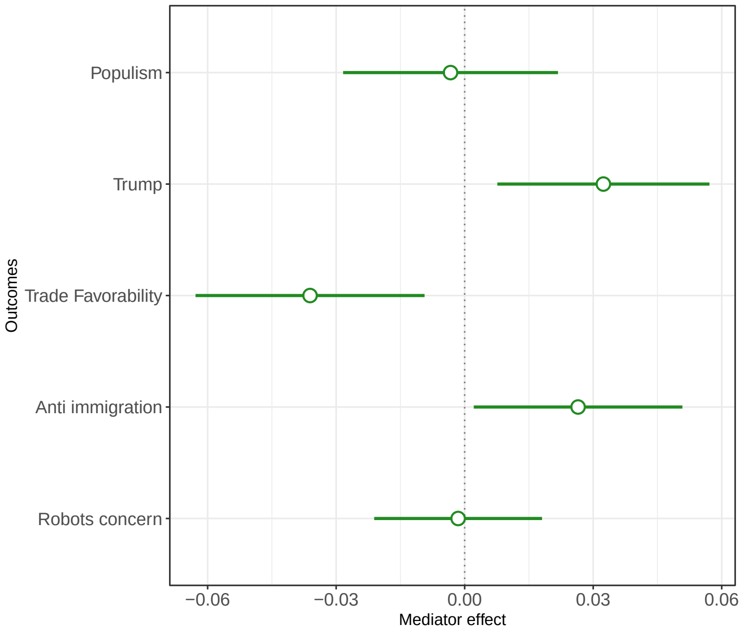

Figure 4: Encouragement Effects on Outcomes, Matching

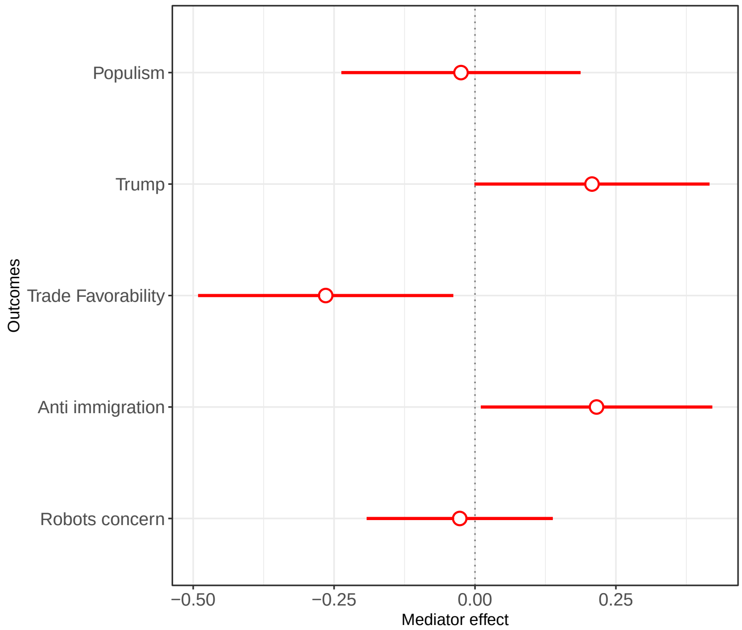

Figure 5: Mediator Effects on Outcomes, ITT

Note: All outcomes were transformed into binary, coded as 1 or 0.

[23] I employ an alternative approach to determine high levels of the mediator by assessing the probability that the observed level of cultural grievance under encouragement equals the expected level of cultural grievance under non-encouragement. Appendix C.3 provides a detailed discussion of this approach, including the incorporation of diverse definitions of high levels within comparable groups based on education, gender, and race. The results remain consistent across variations, as illustrated in Figures C.6-C.12.

[24] I redefined the threshold as the 75th percentile, and 25th percentile, and the results remained consistent. For further details refer to the Appendix C.2.

Combining the treatment effect on the mediator (Figure 3) and the mediator's effect on the outcome (Figure 5), I can readily calculate the causal mediation effect as the product of these coefficients, and estimate the standard errors with the Delta Method (refer to Appendix C.5 for further explanations.). The causal mediation effect translates into an approximately 6.3 percentage-point increase in support for Trump, a 6.5 percentage-point increase in anti-immigration attitudes, and an 8.1-point decrease in trade favorability (see Figure C.14). These effects are statistically significant at conventional levels, with the exception of the support for Trump.[25] To contextualize these findings, I focus on changes in illiberal policy preferences. The mediated effect accounts for about one-third of the total change in anti-immigration attitudes, while 43% in the total decline in trade. These results support **Hypothesis** 3, which posits the existence of a mediated path through which automation influences politics.

Furthermore, the encouragement of the mediator does not appear to have an impact on populist attitudes. As a result, all observed effects can be attributed to the direct effect of exposure to automation or to other unspecified mechanisms. In the context of support for Trump, my analysis indicates that the cultural pathway primarily accounts for any post-exposure effect. There's also a plausible scenario in which the direct effect of automation on populism contributes to the support for Trump, although this dynamic is beyond the scope of the current project's design.

The preceding analysis demonstrates that exposure to automation risk affects cultural grievances and subsequently influences political behavior. As a result, these findings offer insights into cultural grievances as a potential mechanism explaining why exposure to automation risk triggers support for populism and prompts illiberal policy preferences. To enhance the robustness of these effects, I also estimate the causal mediation effect using model-based inference. In this approach, I rely on observed values of cultural grievance proxies rather than random assignment to the encouragement (i.e., a design-based approach).[26]

To establish a mediated effect, I first confirm the relationship between the automation risk treatment and cultural grievances (as previously discussed; see Figure 3). Next, I estimate the impact of the mediator on the political outcomes, as presented in Figure C.15 in the Appendix. Finally, the combined findings from these steps are used to infer the proportion of the total effect

[25]The estimated effect on support for Trump is less precise, but an 85% CI does not cover zero.
[26]For greater discussion of the model-based analysis, refer to the Appendix.

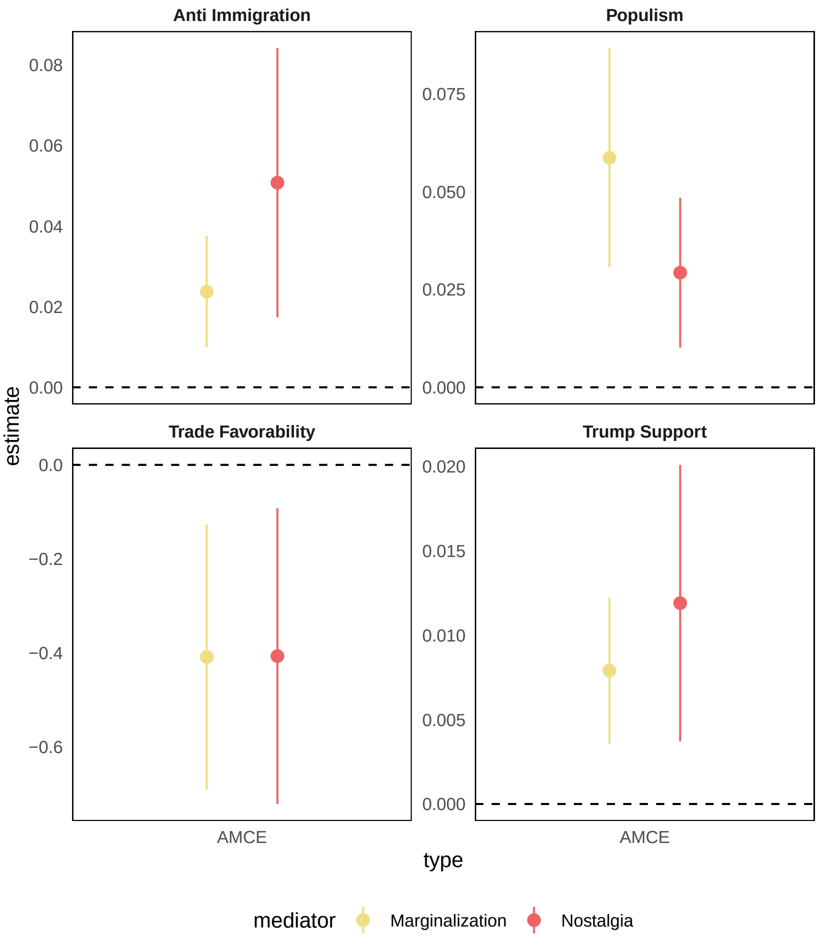

Figure 6: Model-based Estimates of Causal Mechanisms

of automation risk, relying on causal mediation analysis by Imai et al. (2011). The summarized results are shown in Figure 6, and they align with the design-based analysis findings.[27]

The effect can be illustrated by examining trade favorability. I observe a direct effect of automation risk triggering preferences toward more illiberal policies, such as anti-trade, but the total effect is higher as a result of a proportion of this effect going through the mediator. In particular, around 11 percent of the total decline in trade favorability—captured as the perception that trade negatively affects American workers—can be attributed to cultural grievances. Similarly to the experimental results, the decomposition of the total effect on Trump suggests that any potential impact operates primarily through the mediator rather than being a direct result of exposure to automation risk. Furthermore, in contrast to the experimental results, the model-based inference indicates that populist attitudes are also mediated through cultural grievances.

[27] See Figure C.16 for the direct and mediated effects plotted together, and Table C.3 with the sensitivity of the results to violation of the sequential ignorability assumption.

Study 2: Observational Cross-Sectional Evidence

In this section, I show that the mechanisms uncovered in my experimental analysis have external validity by conducting an observational study. I test my core hypotheses using data from waves 1–7 (2002–2016) of the European Social Survey (ESS), and for the mediation analysis, waves 6 and 7. I include thirteen West European countries.[28] In this analysis, the dependent variable is the vote choice for radical right parties. The classification of populist radical right parties adheres to the criteria established by previous researchers. Examples of such parties within the sample include AfD (Germany), UKIP (United Kingdom), and the Front National (France).

The ESS offers comprehensive occupational information through the International Standard Classification, which allows me to gauge individual-level risk exposure to automation.[29] This approach operates under the assumption that individual occupations and tasks play a significant role in determining exposure to automation risk (e.g., Autor, 2013). In particular, the independent variable is an occupation's probability of computerization, developed by Frey and Osborne (2017) using a Gaussian process classifier. The authors argue that "computerization is now spreading to domains commonly defined as non-routine" (p.258), and their measure has the uniqueness of providing an estimate of what recent technological change is likely to mean for the future of employment.

This measure ranges from 0 to 1, with 0 representing no probability of computerization (e.g., recreational therapists), and 1 representing a fully computerizable task (e.g., telemarketers). As an alternative, I use Anelli, Colantone, and Stanig 2021's proxy for robot adoption. It combines individual vulnerability with robot stock changes over the last two years, using International Federation of Robotics (IFR) data. I also replicate the analysis with Anelli et al.'s (2021) individual automation exposure measure, predicting probabilities based on individual attributes and pre-automation employment composition at the occupation level.

Turning to the mediators, one challenge is that the ESS survey questions do not perfectly match my own survey questions from the experiment. Therefore, I rely on closely related mediators taken from published research. The feelings of marginalization that lead voters to support radical right-wing parties and candidates are likely associated with the belief that

[28]The countries are Austria, Belgium, Finland, France, Germany, Italy, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, and the United Kingdom.

[29]I constructed the independent variable utilizing the International Standard Classification of Occupations (ISCO-08 and ISCO-88). ISCO-08 occupations from the 6th wave of ESS were transformed to ISCO-88 using Thewissen and Rueda (2019)'s harmonization method. Furthermore, I linked each subject to the 2010 Standard Occupational Classification (SOC) based on Thewissen et al.'s (2019) conversion.

one's privileged status in society is threatened by "outsiders." To capture this perceived threat from outsiders, I use indicators of anti-immigration attitudes from three questions (e.g., Hays, Lim, and Spoon, 2019; Carreras, Irepoglu Carreras, and Bowler, 2019). The first question evaluates perceptions of cultural threats, asking respondents whether immigrants "undermine or enrich the country's cultural life".The second question investigates the perceived impact of immigration on the economy, inquiring whether it is "bad or good for the country's economy." The third question explores whether immigrants make the country a "worse or better place to live." Respondents' answers to these questions are captured on an 11-point scale, where 0 signifies negative viewpoints (e.g., a worse place to live), and 10 represents positive perspectives (e.g., a better place to live).

To proxy nostalgia, I employ two questions. The first one evaluates respondents' difficulty in maintaining hope about the world's future. The second question gauges the extent of agreement with the statement, "For most people in this country, life is getting worse." Respondents provide answers on a scale ranging from (1) "strongly agree" to (5) "strongly disagree." These questions are only available for the years 2006 and 2012. It is important to acknowledge that these proxies offer an imperfect assessment of nostalgia, as they primarily capture collective sentiments rather than individual levels, and they reflect more of a pessimistic outlook on the future rather than a longing for a better past. However, previous research has effectively employed these survey questions to evaluate nostalgia (e.g., Steenvoorden and Harteveld, 2018).

The literature on political behavior discusses several other factors that may affect individuals' vote choices. Thus, I include individual-level controls for age, sex, years of education, location, being an ethnic minority, and employment characteristics (e.g. Frey, Berger, and Chen, 2017; Gingrich, 2019; Thewissen and Rueda, 2019). The model also includes changes in the stock of robots, unemployment rates, and immigrant exposure at the regional level.

Estimation Strategy

To explore the mediated effects of exposure to automation risk through cultural grievances, I replicate the methodology detailed in the experimental section, which involves causal mediation analysis. I begin by examining the link between automation risk and support for the radical right. Subsequently, I investigate the correlation between exposure to automation and the mediators. Lastly, I implement causal mediation analysis as outlined by Imai et al. (2011).

The main challenge inherent in mediation analysis, particularly when applied to observational data, revolves around the potential violation of the sequential ignorability assumption (Imai et al., 2011; Keele, Tingley, and Yamamoto, 2015). This assumption rests on two conditions. First, given the observed pretreatment covariates (e.g., age), the treatment (automation) must be independent of both the outcome and the mediator. Second, the observed mediator (cultural grievances) should be independent of the outcomes, conditioned on the observed treatment and pretreatment covariates. Unfortunately, this assumption cannot be tested using observed data, but I will: i) incorporate multiple pretreatment confounders such as gender, age, and education, as well as regional (NUT2 level) and country-year characteristics into the model; ii) employ the sensitivity analysis method proposed by Imai et al. (2011). This method allows me to quantify the extent to which violations of the sequential ignorability assumption would affect the interpretation of the mediation results.

Observational Evidence for Exposure to Automation on Politics and Mediators

My findings support the theoretical framework and are consistent with the results of the experimental analyses. As expected, exposure to automation risk significantly increases voters' probability of supporting a radical right party (Table 1, column 1). For example, when the probability of computerization is at its minimum value (0 for recreational therapists), the probability that the individual will vote for a populist party is 0.006. At the other extreme, when the probability of computerization is at its maximum value (1 for telemarketers), the probability of choosing a populist right candidate at the next election is 0.18.[30]

Columns 2 to 4 relate to **Hypothesis 2**, which indicates that increased exposure to automation risk corresponds to increased feelings of marginalization and nostalgia. The negative coefficients suggest that greater automation risk is associated with less tolerance for immigrants, consistent across the three operationalizations. At the extreme ends of the risk distribution (0 to 1 probability of computerization), more automation risk corresponds to an approximate decrease of 2.37–1.98 units on a 11-point scale in an individual's inclination to embrace immigrants within their culture, economy, and country.[31] Turning to the relationship between exposure to automation risk and nostalgic sentiments, columns 5 and 6 reject the null hypothesis of no relationship for both operationalizations of nostalgia. The negative coefficients show that a

[30] Figure A.3 presents the predicted values for these outcomes.
[31] See Figure A.4 for marginal effects.

higher likelihood of computerization is associated with lessened hopes about the future. Moving from 0 to 1 in computerization probability decreases future optimism by 0.72–0.73 points on a 5-point scale, thus increasing nostalgic sentiments by roughly 14.6%.

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Frey & Osborne	3.503***	-2.376***	-2.315***	-1.987***	-0.718***	-0.735***
	(0.231)	(0.100)	(0.094)	(0.095)	(0.052)	(0.058)
Demographic	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	64440	151296	150778	151615	44674	44923
$R^2(p)$	0.174	0.162	0.116	0.136	0.294	0.134
AIC	2.7e+04	6.7e+05	6.6e+05	6.5e+05	1.2e+05	1.3e+05

Standard errors clustered by region-year in parentheses

$(^{*})p < 0.1$, $(^{**})p < 0.05$, $(^{***})p < 0.01$

Table 1: Automation, cultural attitudes, and vote choices.
Dependent variable: (1) Support for populist radical right. (2-4) Level of agreement with immigration as better for culture, economy and life. Answers range from “Not like me at all” ($= 0$) to “Very much like me” ($= 10$). (5-6) Level of agreement with “life is getting worse” and “hard to have hope about the future.” Answers range from “Agree strongly” ($= 1$) to “Disagree strongly” ($= 5$). Source: ESS (1-7) data.

The findings remain consistent across multiple alternative specifications. Initially, I include an extra regional-level predictor—changes in robot exposure measured by the variation in robot quantity per thousand workers over the past three years, using data from the International Federation of Robotics and methodology from Anelli, Colantone, and Stanig (2021). Table D.4 confirms that both individual risk exposure and regional robot presence are statistically significant.

Then, I add several control variables to the previous models that the literature on voting behavior suggests may affect vote choice and individual attitudes (e.g. Frey, Berger, and Chen, 2017; Gingrich, 2019; Thewissen and Rueda, 2019; Hays, Lim, and Spoon, 2019). At the individual level, I add dummy variables for being foreign-born, living in a city (urban), and being an ethnic minority. Then, I incorporate three dummy variables representing respondents' experience in the labor market: i) unemployed, ii) union membership, and iii) limited employment contract, which reflects some degree of precariousness in the respondent's linkages with the job.[32] Finally, I incorporate into the models two additional regional-level variables: i) immigrant exposure, proxied as the proportion of foreign-born respondents in the region, and ii) regional unemployment, calculated as the share of unemployed respondents in the region. I expect respondents in regions with high unemployment and immigrants to be more likely to hold anti-

[32]The results remain the same if I exclude employment variables, which arguably may also be post-treatment.

immigration attitudes, nostalgic sentiments, and support populist right candidates. Regarding the regional-level variables, while unemployment may increase anti-immigrant propensity and nostalgic views, the expectations regarding immigration exposure are less clear. Previous scholars have argued that it can either decrease outgroup threat predispositions or exacerbate them (Inglehart, 2018; Norris, 2004). The results remain similar across these model specifications (see Table D.5)

To assess i) whether current occupations may mask past automation dynamics (e.g., a worker that has already been displaced) and ii) the interaction of individual and regional exposure, I re-estimate previous models relying on the measure proposed by Anelli, Colantone, and Stanig (2021) as the independent variable. It is based on the predicted probabilities for an individual to be occupied in high-automatability occupations and the incorporation of robots in an individual's region. Tables D.6, and D.7 (with and without control variables) show the estimations. The results remain unchanged. A one-SD increase in individual exposure to automation leads to a decrease of about 0.31–0.26 units in pro-immigration predisposition (11 points-scale) and a decrease of about 0.14–0.12 in nostalgic sentiments (5 points-scale).

To examine the link between cultural grievances and voting choices, I start with logistic regression models explaining voting choice by automation risk, mediators, and other demographic controls (refer to Table D.8).[33] All estimated coefficients displayed statistical significance and aligned with the expected direction. In the subsequent section, I further analyze this relationship by conducting a causal mediation analysis. This analysis treats exposure to automation risk as the treatment, cultural grievances (marginalization and nostalgia) as mediators, and support for the radical right as the outcome variable.

Observational Evidence for Causal Mechanisms

Results consistent with both my theory and the experimental outcomes concerning average mediation causal effect (AMCE) and average direct effect (ADE) are presented in Figure 7 and Figure 8. Yellow (red) points denote point estimates for the marginalization (nostalgia) hypothesis, accompanied by 95% confidence intervals generated using simulations from a robust variance-covariance matrix. All these estimates exhibit a positive trend, leading to the rejection of the null hypothesis of no relationship. This lends support to **Hypothesis 3**.

[33] Comparable models were replicated in Tables D.9, utilizing robot adoption in different countries as an instrumental variable for robot exposure (Anelli, Colantone, and Stanig, 2021). The results remained consistent.

The magnitude of the effects of automation, mediated through cultural grievances, on support for the populist right encompasses an increase of roughly 3.5 percentage points and 1 percentage point (anti-immigration attitudes and nostalgia, respectively). To contextualize these findings, the total impact of automation on support for the radical right is roughly 12.5 percentage points when comparing a probability shift from 0 to 1. Of this impact, approximately 30 percent is mediated by anti-immigrant sentiments, influencing support for the populist right, while nostalgia accounts for a 13 percent contribution.

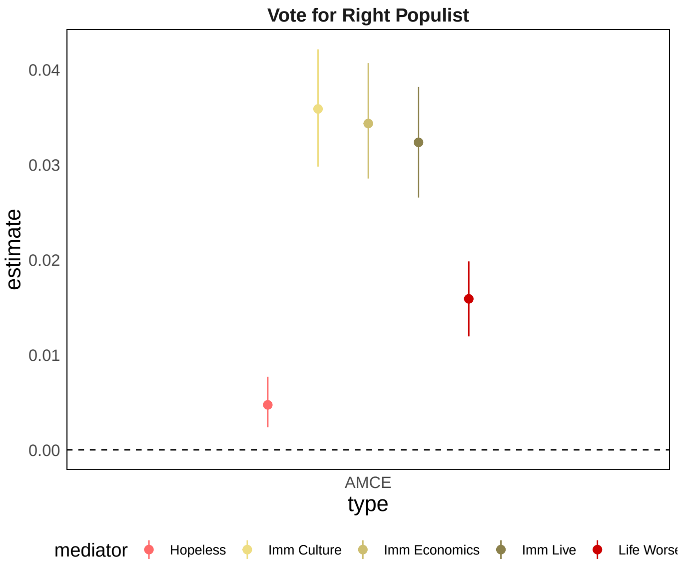

Figure 7: Mediated effect of automation through cultural beliefs on political behavior.

Source: ESS 6-7

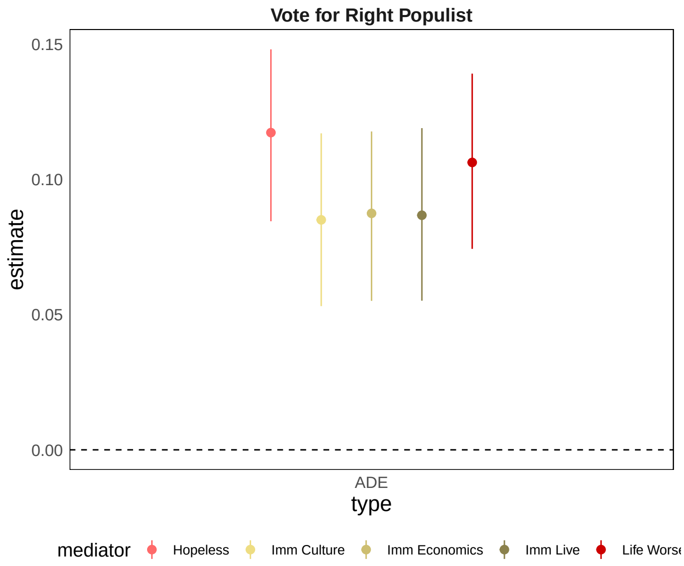

Figure 8: Direct effect of automation on political behavior.

Source: ESS 6-7

As a robustness check, I estimated different model specifications, i) varying the inclusion of pre-treatment variables (some or the full battery) and ii) using two operationalizations of the independent variable: the probability of computerization provided by Frey and Osborne (2017), and the individual exposure to automation measured by Anelli, Colantone, and Stanig (2021). Tables D.10-D.13 present the results of the second stage of the mediated models. Results remain unchanged for all the model specifications.

Table D.14 presents the sensitivity of the results (ρ) to violations of the sequential ignorability assumption. This analysis identifies the correlation between the residuals of the mediator equation (ϵ_{i2}) and the residuals of the outcome equation (ϵ_{i3}) that would render the point estimate of the ACME zero. For immigration, a correlation of approximately 0.4 between the residuals would nullify the ACME. Similarly, for nostalgia, a correlation of 0.1 between omitted confounders would be required to nullify the ACME for both dependent variables. Essentially, if the explanatory power of the omitted confounders surpasses all the included variables, the mediated effect becomes indistinguishable from zero. While such a scenario is possible, it seems unlikely.

Summary of Results

To collectively summarize the findings of these studies, the experimental manipulations demonstrate that exposure to automation risk leads to notable changes in political behavior, specifically an increase in populist attitudes and illiberal political preferences. Notably, automation risk triggers a sense of marginalization and nostalgic sentiment. Each study confirms these relationships, highlighting the link between economic threats and cultural beliefs. The results further reveal that feelings of marginalization and nostalgia partially mediate the relationship between the automation risk treatments and political beliefs and behaviors. These patterns are consistent across the observational study as well. All the studies indicate that cultural grievances play a significant role in understanding the political consequences of exposure to automation risk.

The consistency in results across observational and experimental methods indicates that the findings extend beyond the experimental setting, underscoring the complex effects of technological change on both material well-being and cultural attitudes. The current wave of technological change is substantially transforming labor market structures, affecting various aspects of life, including economic outcomes and cultural grievances. These findings hold crucial implications for democracy, given that individuals adversely impacted by automation are more inclined to back political parties that advocate exclusionary policies, thereby potentially undermining democratic institutions.

Conclusion

This article has provided a theoretical framework and empirical evidence to understand the interplay between economics and culture in order to comprehend the rise of populism. The argument put forth suggests that technological change has both a direct and an indirect impact on politics, mediated by changes in individuals' cultural grievances. By employing a multimethod approach that combines survey experiments and observational cross-sectional analysis, I find that there is a causal relationship between exposure to automation and political attitudes. Exposure to automation risk increases the likelihood of adopting populist attitudes and endorsing illiberal preferences, such as anti-globalization and hostility toward immigrants. Additionally, this study shows that exposure to automation risk leads to changes in perceptions of marginalization and nostalgia, which, in turn, affect political beliefs and behaviors. Overall, this work improves our understanding of why vulnerable workers shift their support towards radical-right parties.

There is still much work to be done in exploring the role of technological change and cultural beliefs. This study limited its analysis to two operationalizations of cultural grievances, namely marginalization and nostalgia. Future research should expand the analysis to encompass other manifestations of cultural grievances. Additionally, investigating heterogeneous effects by considering pre-existing conditions such as race, class perception, and income levels would be valuable.

There are also numerous opportunities for follow-up studies related to the experimental design. This study provides a template for unpacking mechanisms in political science. Yet, challenges remain with respect to identifying causal mechanisms solely through the encouragement of mediators. My work proposes an important innovation for encouragement designs: assessing compliance based on subjects' task performances. Moving forward, for example, one could evaluate the content quality of subjects' open-ended responses to assess compliance.

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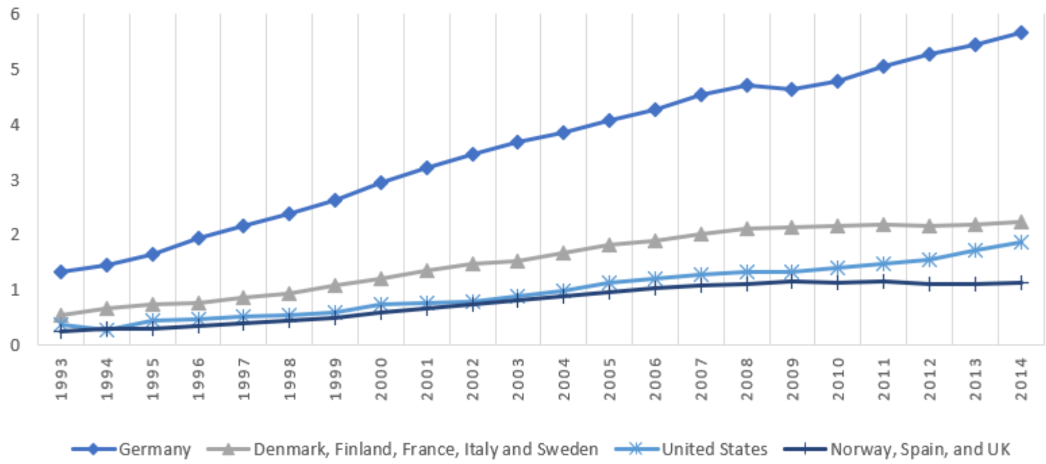
Online Appendix

Contents

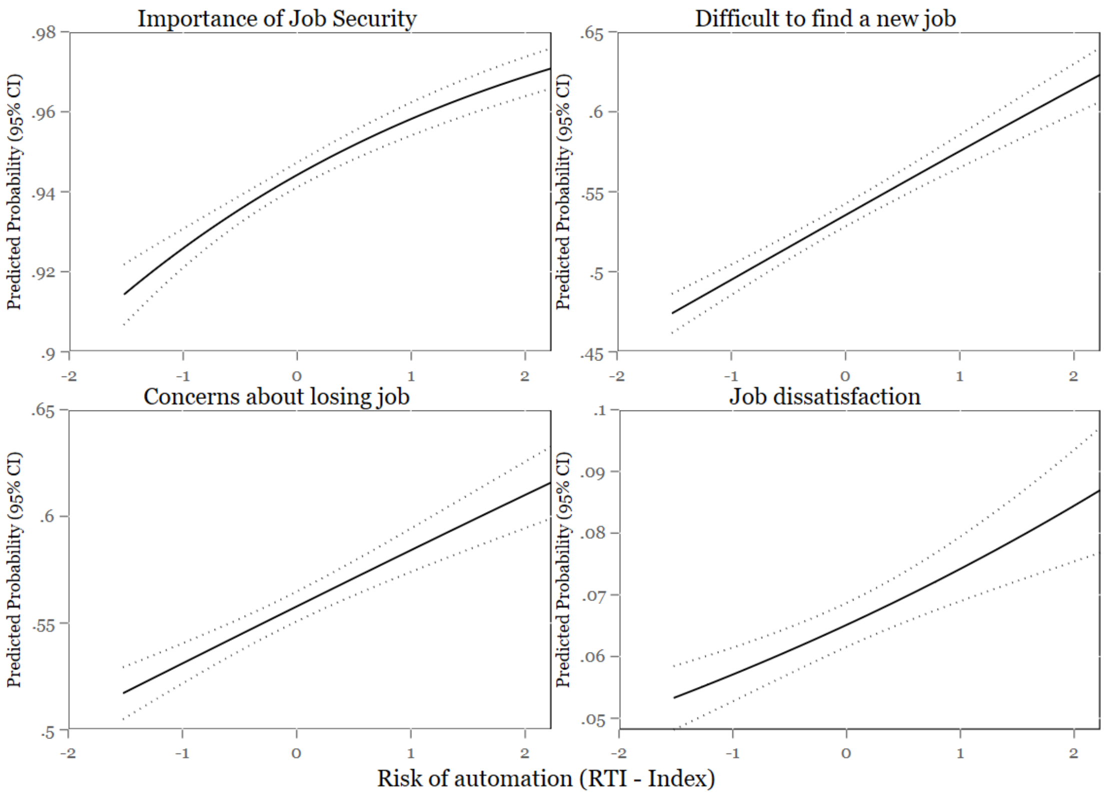
A Additional Figures

Figure A.1: Stock of robots per thousand of workers base 1993



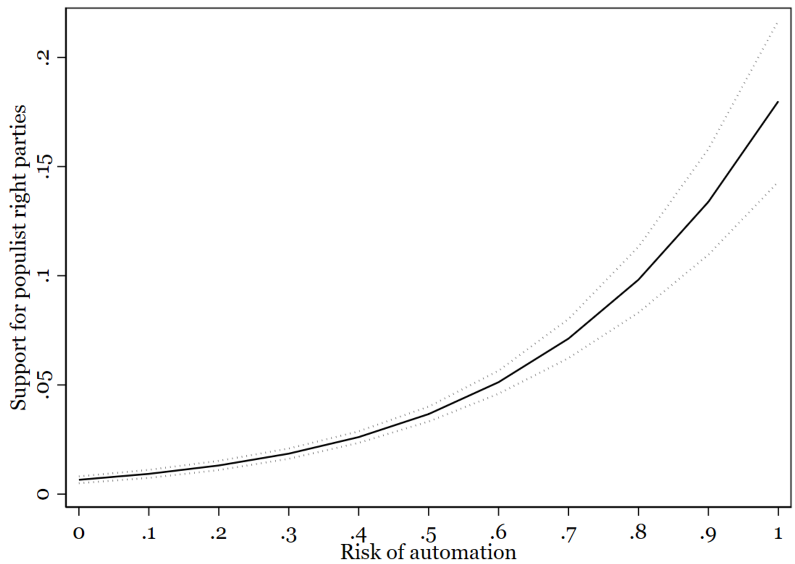
Source: Replication of Acemoglu (2020) with data from the IFR.et al.

Figure A.2: Importance of job security, Difficulties to find a new job, Concerns about losing the job and Job dissatisfaction



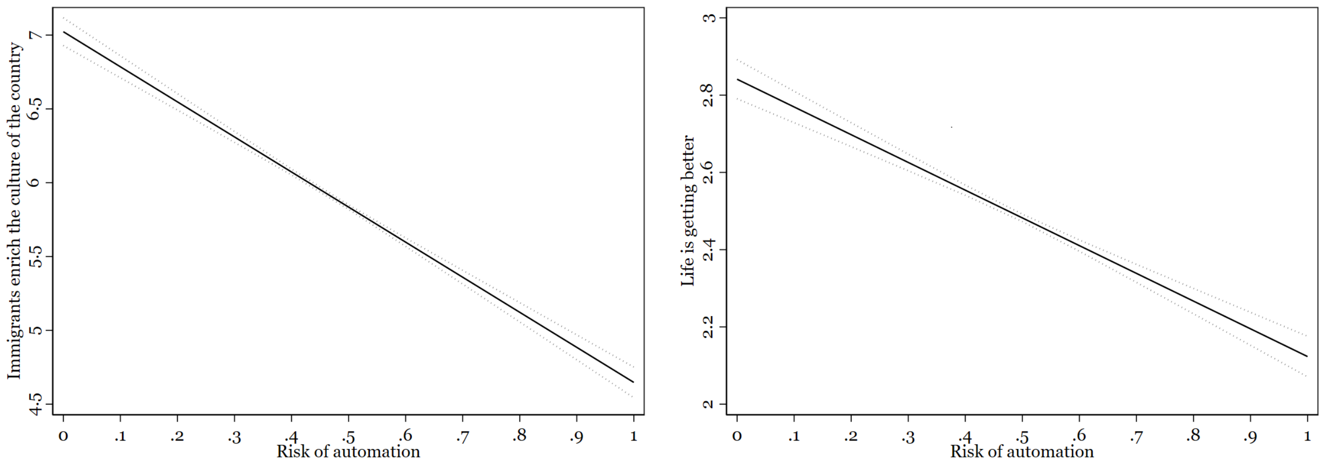
Source: ISSP (1997, 2005 and 2015)

Figure A.3: Marginal effects of Automation on voting behavior



Source: ESS (1-7)

Figure A.4: Marginal effects of automation on hostility toward immigrants and nostalgia



Source: ESS (1-7)

B Survey

B.1 Pre-Registration

Refer to Pre-registration OSF (3KDPQ) to access the Survey Questionary.

Visit https://osf.io/q49en.

B.2 Descriptive statistics

In terms of representativeness, my sample comprises approximately 71% white participants, aligning closely with the 2016 voter demographics—according to CCS, white voters constituted approximately 74% of the 2016 electorate. The mean age within my sample hovers around 44, mirroring the average age of 2016 voters. When analyzing the age and race distribution of our sample based on political affiliation, the patterns also closely resemble what's expected. Therefore, while the extent of the applicability of our findings to the wider U.S. voting populace hinges on how well our online convenience sample reflects broader demographics, these descriptives show that the sample does not significantly deviate from key demographic characteristics of this population.

	Mean	Median	S.D.	Min.	Max	Obs.
% Female	55.44	100.00	49.71	0	100	3133
% White	71.47	100.00	45.17	0	100	3133
Income	7.79	8.00	3.45	1	14	3133
% Unemployed	8.55	0.00	27.97	0	100	3133
% Bachelors	0.61	1.00	0.49	0	1	3133
Age	44.25	42.00	12.20	20	88	3133
Ideological spectrum	4.47	5.00	2.97	0	10	3133

Table B.1: Descriptive statistics pre-treatment variables.
Income is an ordinal scale from 1 (less than $10,000) to 14 (greater than $200,000), where 5 is $40,000–49,999.
Ideological Spectrum is an ordinal scale from 1 (Very Liberal) to 10 (Very Conservative), where 5 is Moderate

	Mean	Median	S.D.	Min.	Max	Obs.
% Definitely support Trump 2024	13.25	0.00	33.90	0	100	3133
Anti-Elitism	4.07	4.00	1.00	1	5	3129
Nostalgia Index	10.08	10.00	3.11	3	15	3133
% High Nostalgia	34.92	0.00	47.68	0	100	3133
Marginalization Index	9.09	9.00	3.23	3	15	3133
% High Marginalization	36.00	0.00	48.01	0	100	3133
Anti Immigration	3.01	3.00	1.21	1	5	3133
Trade Favorability: American Workers	46.16	48.00	26.09	0	100	3133
% High Trade Favorability	46.89	0.00	49.91	0	100	3133
Concerns about Robots Index	14.77	15.00	4.21	5	25	3103

Table B.2: Descriptive statistics outcome variables.
Anti-Elitism is measured on an ordinal scale from 1 (strongly disagree with anti-elite statement) to 5 (strongly agree). The nostalgia index incorporates three statements assessing nostalgia, scored from 1 (low) to 5 (high), with higher numbers indicating greater levels of nostalgia. Similarly, the marginalization index consists of three statements evaluating marginalization, also scored from 1 (low) to 5 (high). Anti-immigration sentiment is assessed on an ordinal scale from 1 (strongly disagree with the anti-immigration statement) to 5 (strongly agree). Trade favorability is rated on a scale from 1 (trade is very bad) to 100 (trade is very good). The concerns about robots index encompasses five questions related to apprehensions about robots and artificial intelligence, rated from 1 (low) to 5 (very concerned).

C STUDY 1, CAUSAL MEDIATION ANALYSIS

C.1Effects of T on M

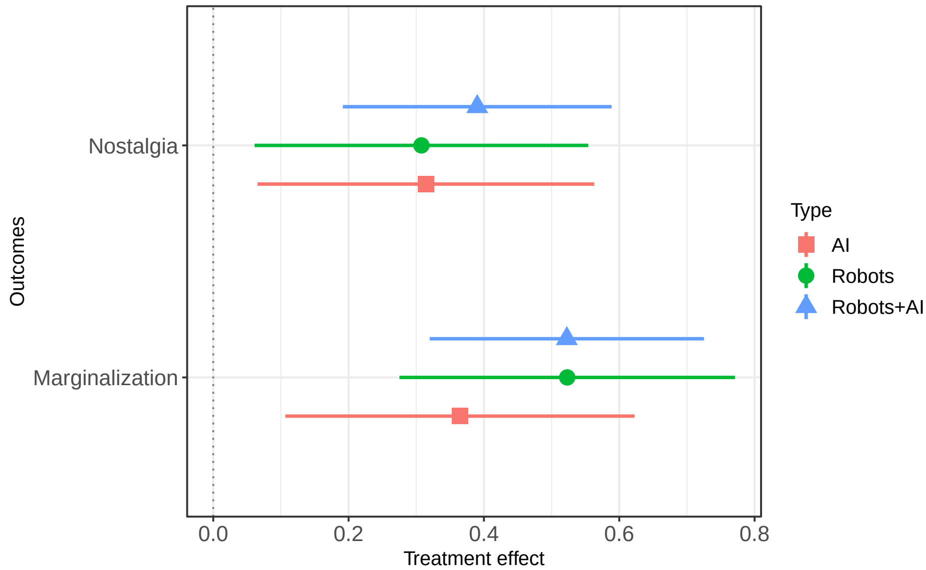


Figure C.5: Treatment Effects of Exposure to Automation Risk on mediators.

Note: The 'nostalgia' and 'marginalization' indices are derived from the sum of various questions, resulting in a range of 3 to 15.

C.2 ITT - compliers & task efforts

To estimate compliance, I have integrated data related to the effort expended on the writing task as an indicator of task completion. Specifically, I have examined the number of words generated by the subjects during the task. In order to ensure the robustness of the results, I have employed various thresholds to determine task completion.

These thresholds encompass the 25th percentile, with a requirement of at least 38 words written, the 50th percentile with a minimum of 58 words, and the 75th percentile, necessitating a minimum of 85 words written. Importantly, the findings from these different thresholds consistently support the conclusions drawn from the analysis. This multi-threshold approach enhances the reliability and validity of the compliance estimation within the study.

C.3 ITT - compliers & higher levels of the mediator

In the context of addressing compliance issues, I employ an alternative strategy to assess the significance of high mediator levels. This approach aims to determine whether the probability that the observed level of cultural grievance under encouragement matches the expected level under the control group.

I calculate t-statistics, which represent the probability for an individual denoted as i to exhibit a higher level of cultural grievances under encouragement, using the following formula:

$$\frac{\text{(Cultural Grievance Observed Under Encouragement for } i - \text{Mean Cultural Grievance Under No Encouragement)}}{\text{(Standard Deviation of Mean Cultural Grievance Under No Encouragement)}}$$

To establish a theoretically meaningful threshold, I consider the associated probability. This involves assuming that the sampling distribution for the mean cultural grievance under the control condition is a normal distribution. Consequently, I employ a simple t-test to compute p-values for each of the observed values in the encouragement group as indicators of whether these were high levels.

In summary, this alternative measure of compliance integrates two key factors: 1) task completion (whether participants completed the exercises) and 2) elevated levels of cultural grievances, assessed through the probability that the observed mediator value in the encouragement group differs (higher) from that of individuals who did not receive encouragement.

Figure C.6 shows that the results remain unchanged.

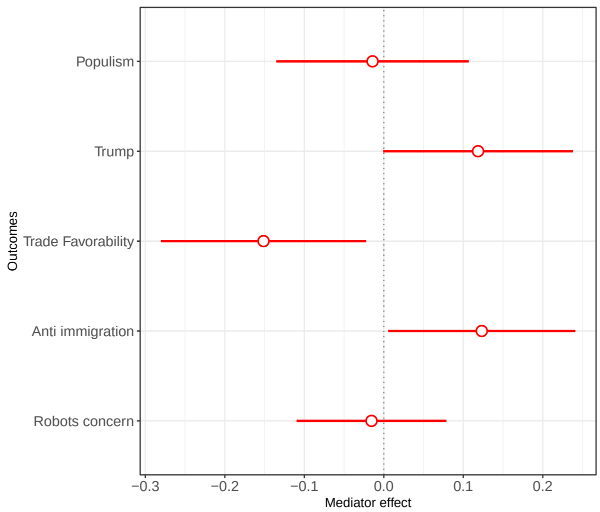


Figure C.6: T=0.842 (p-value<0.4)

C.3.1 Heterogeneity and compliers

Furthermore, I incorporate pretreatment covariates as a baseline to estimate the parameters of the sampling distribution. This approach enables the consideration of "encouragement heterogeneity" by conditioning on factors such as gender, education, and race, thereby providing a more nuanced understanding of complier estimation.

In essence, instead of solely examining parameters for the entire sample, I create eight groups by combining three characteristics: white vs. non-white, college vs. no college, and female vs. male. For each of these groups, I calculate the mean of cultural grievances and repeat the process of comparing the encouraged and non-encouraged groups.

Importantly, the results remain consistent, regardless of the strictness applied in defining high levels of the mediator. Figures C.7-C.12 present the results while varying the criteria for defining high mediator levels.

Overall, this method offers a theoretically grounded and less arbitrary approach to identifying compliers within the studied population.

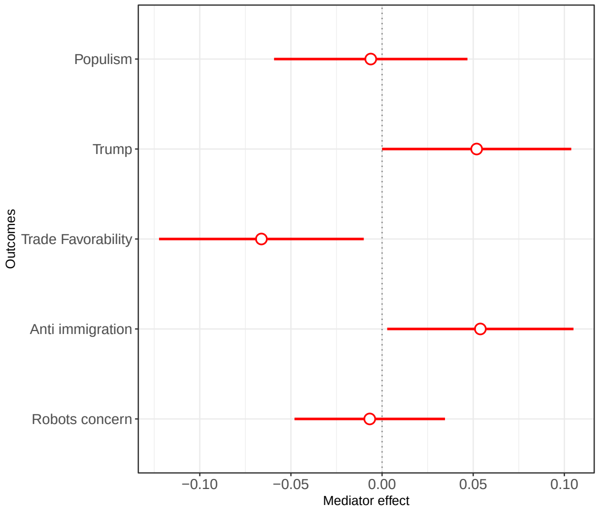


Figure C.7: T=0.18 (p-value<0.5)

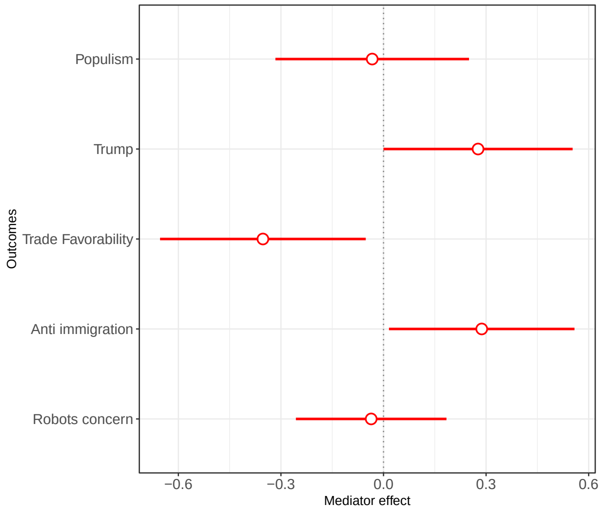


Figure C.10: T=1.646 (p-value<0.1)

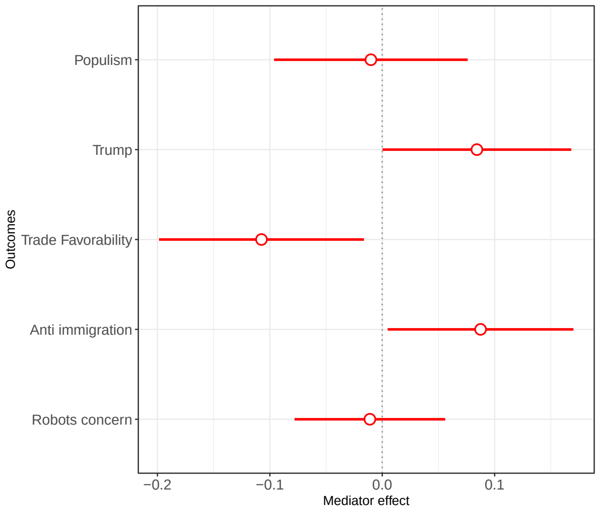


Figure C.8: T=0.842 (p-value <0.40)

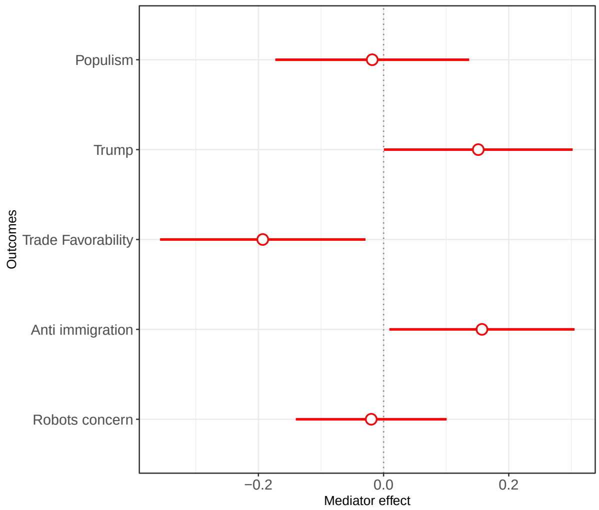


Figure C.11: T=1.282 (p-value <0.20)

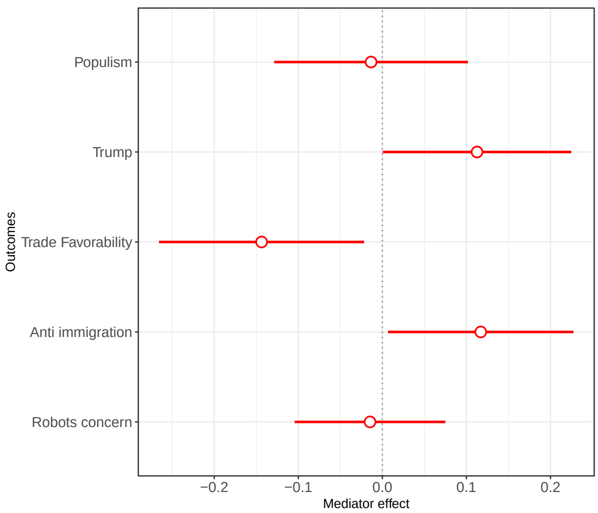


Figure C.9: T=1.036 (p-value<0.3)

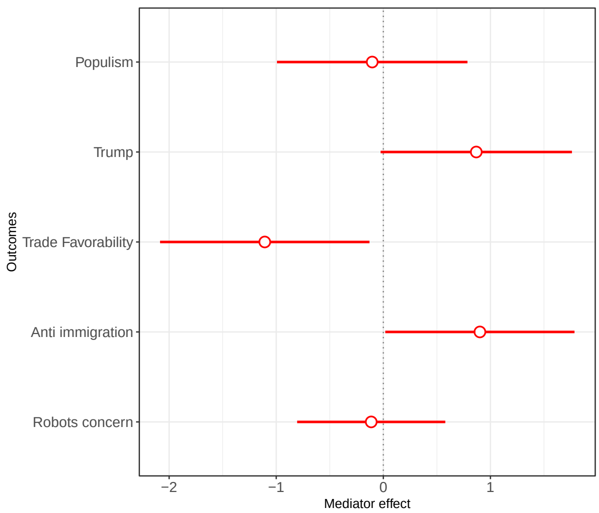


Figure C.12: T=1.962 (p-value <0.05)

C.4 Bounds

Following Balke and Pearl (1997), and after implementing linear programming optimization techniques, I define bounds using the following equations:

$$= max \begin{Bmatrix} p_{00.0} + p_{11.1} - 1, \\ p_{00.1} + p_{11.1} - 1, \\ p_{11.0} + p_{00.1} - 1, \\ p_{00.0} + p_{11.0} - 1, \\ 2p_{00.0} + p_{11.0} + p_{10.1} + p_{11.1} - 2, \\ p_{00.0} + 2p_{11.0} + p_{00.1} + p_{01.1} - 2, \\ p_{10.0} + p_{11.1} + 2p_{00.1} + p_{11.1} - 2, \\ p_{00.0} + p_{01.0} + p_{00.1} + 2p_{11.1} - 2 \end{Bmatrix}$$

$$= min \begin{Bmatrix} 1 - p_{10.0} - p_{01.1}, \\ 1 - p_{01.0} - p_{10.1}, \\ 1 - p_{01.0} - p_{10.1}, \\ 1 - p_{01.1} - p_{10.1}, \\ 2 - 2p_{01.0} - p_{10.0} - p_{10.1} - p_{11.1}, \\ 2 - p_{01.0} - 2p_{10.0} - p_{00.1} - p_{01.1}, \\ 2 - p_{10.0} - p_{11.0} - 2p_{01.1} - p_{10.1}, \\ 2 - p_{00.0} - p_{01.0} - p_{01.0} - p_{01.1} - 2p_{10.1} \end{Bmatrix}$$

Figure C.13 presents the bounds, which are not informative.

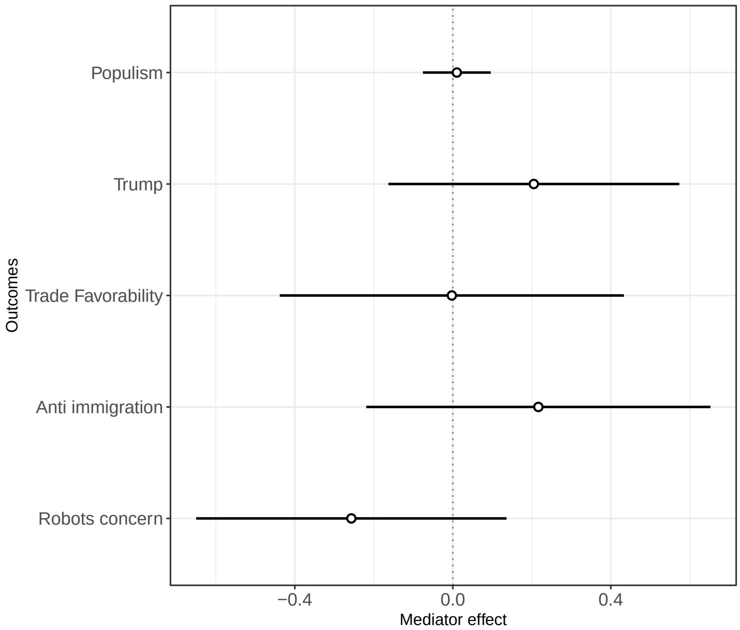


Figure C.13: Mediator Effects on Outcomes, Bounds

C.5 Causal Chain and Delta Method - Average Causal Mediation Analysis

After estimating the effects of the treatment on the mediators, and the effects of the mediators' encouragement on the political outcomes (ITT) I use the Delta Method, in order to approximate probability distribution for the multiplication of two parameters.

Let p_1 be the effects of the treatment on mediators, and p_2 be the effects of the encouragement of the mediator, then the causal mediation effect ($Y_i(t, M_i(1)) - Y_i(t, M_i(0))$) can be estimated under the assumption of homogeneous treatment effects as $p^1 \times p^2$. Then, we can use the **Delta method** to calculate the standard error of $p_1 p_2$. This method states that an approximation of the variance of a function $g(t)$ is given by:

$$\text{Var}(g(t)) \approx \sum_{i=1}^{k} [g_i'(\theta)^2 \text{Var}(t_i)] + 2 \sum_{i>j} g_i'(\theta) g_j'(\theta) \text{Cov}(t_i, t_j).$$

The estimation of the anticipated value of $g(t)$ is expressed as:

$$\mathbb{E}(g(t)) \approx g(\theta).$$

Hence, the expectation corresponds simply to the function, $g(t)$ is defined as $g(p_1, p_2) = p_1 p_2$. Consequently, the expected value of $g(p_1, p_2) = p_1 p_2$ would directly yield $p_1 p_2$. For the computation of variance, it becomes necessary to evaluate the partial derivatives of $g(p_1, p_2)$:

$$\frac{\partial}{\partial p_1} g(p_1, p_2) = p_1$$

$$\frac{\partial}{\partial p_2} g(p_1, p_2) = p_2$$

Thus we get:

$$\text{Var}(p_1 p_2) = p_2^2 \text{Var}(p_1) + p_1^2 \text{Var}(p_2^2) + 2 \cdot p_1 p_2 \text{Cov}(p_1, p_2)$$

$$\text{SE}(p_1 p_2) = \sqrt{p_2^2 \text{Var}(p_1) + p_1^2 \text{Var}(p_2^2) + 2 \cdot p_1 p_2 \text{Cov}(p_1, p_2)}$$

Finally, we can estimate the uncertainty around $p_1 p_2$ using CI formula, and the estimated SE$(p_1 p_2)$

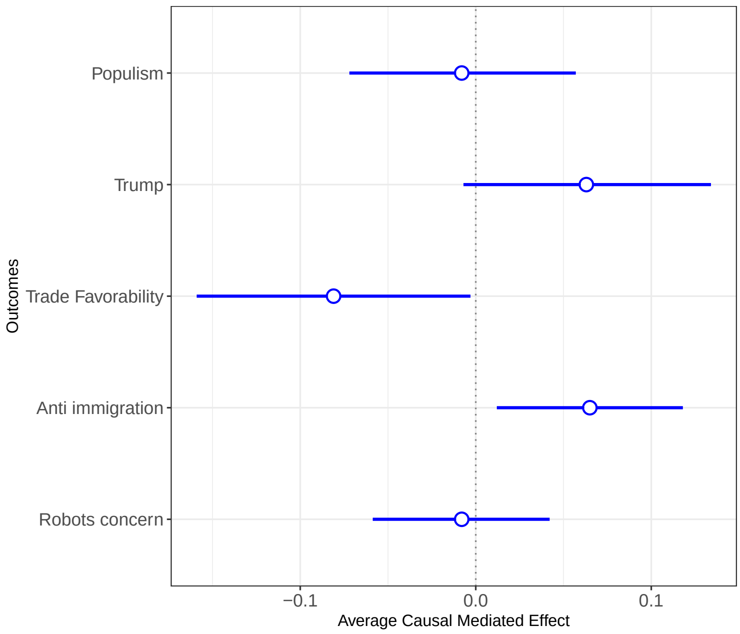


Figure C.14: Causal Mediation Effects

C.6 Model Base Inference with Survey Data

In my study, I design the survey to provide insights into both the effects of exposure to automation risk and the underlying mechanisms driving these effects. I demonstrated earlier that exposure to technological change triggers nostalgia and feelings of marginalization discontent. I refer to these symbolic attitudes as mediators because they mediate the relationship between the treatment variable (exposure to automation) and the final outcome (populist attitudes, support for Trump, and opposition to trade, among others).

The investigation in my study proceeds through three steps. Firstly, estimation is conducted to determine the impact of exposure to automation risk on each of the mediators, as discussed earlier and outlined in equation 4. Secondly, the estimation focuses on evaluating the influence of each mediator on the desired political outcomes by examining the observed values of the mediators, as presented in equation 5. These regressions are controlled for both the treatment variable and potential confounding variables, following the same specification as described in the previous section. Lastly, the combined findings from these steps are used to infer the proportion of the total effect of automation risk, as depicted in Figure 2, that is transmitted through each mediator. Therefore, the model to be estimated in relation to **Hypothesis** 3 can be represented by the following system of equations:

$$Mediators_{irj} = \beta_0 + \beta_1 Automation_i + X_i\beta_2 + \epsilon_{irj} \tag{4}$$

$$Y_{irj} = \beta_0 + \beta_1 Mediators_i + X_i\beta_2 + \epsilon_{irj} \tag{5}$$

where Y_i represents the outcome of interest, for instance, whether individual i developed populist attitudes; $Automation_i$ refers to the treatment of the experiment; $Mediators_i$ is the variable capturing either marginalization of nostalgia; X_i captures various control variables at the individual level such as gender, and occupation and ϵ_{it} is the error term. My theoretical expectations, and demonstrated in the previous section, exposure to technological change will trigger nostalgia and marginalization ($\beta_1 > 0$ in the first equation). Then, from the second equation, when the outcome is populist attitudes, for instance, I expect both mediators to be positively related ($\beta_1 > 0$).

Figure C.15 presents the estimations for the second step of the analysis, with the two mediators, namely feelings of nostalgia and marginalization, as the key independent variables. This figure provides confirmation of the relationship between these mediators and the political outcomes.

However, we have not yet established the presence of a causal pathway between exposure to automation risk and political behavior. To accomplish this, it is necessary to examine the combined effects of exposure to risk on each mediator and the subsequent impact of each mediator on political attitudes. To integrate these components of the causal chain, I employ causal mediation analysis as proposed by Imai et al. (2011). This analytical approach allows

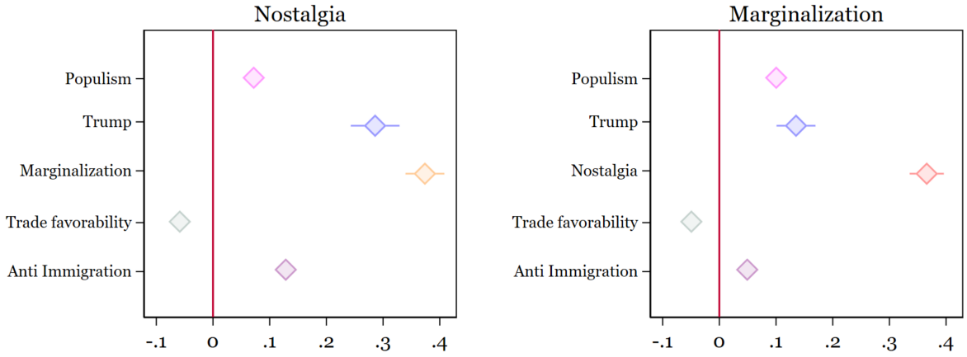


Figure C.15: The Effect of Mediators on Political Outcomes (2nd step)

us to disentangle the average treatment effect (ATE) or total effect into the average causal mediation effect (ACME) and the average direct effect (ADE). While the ATE represents the average difference between the treated and untreated groups, the ACME represents the portion of this effect mediated through the mediators. Figure C.16 presents the estimations for the direct and indirect effects of several outcomes of interest.

This figure presents evidence supporting Hypothesis 3 across all the outcomes of interest. To illustrate this, let's examine the estimations of the relationship between exposure to automation threats and populism (proxied as anti-elitism). The first two coefficients represent the direct effect resulting from random assignment to the automation of jobs treatment. When considering nostalgia (red estimates), the direct effect is positive, indicating an increase in the likelihood of holding populist attitudes after reading the news. Turning to the mediated effect (AMCE), we observe that a portion of the total effect of exposure to automation on populist attitudes operates through triggering nostalgia.

Shifting our focus to marginalization, the ADE is positive, but we cannot reject the null hypothesis of no relationship. In this case, it appears that the majority of the effect occurs through feelings of marginalization rather than a direct influence on populism. Specifically, exposure to automation risk accounts for approximately 26% of this effect by altering feelings of nostalgia and around 25% by influencing perceptions of marginalization.

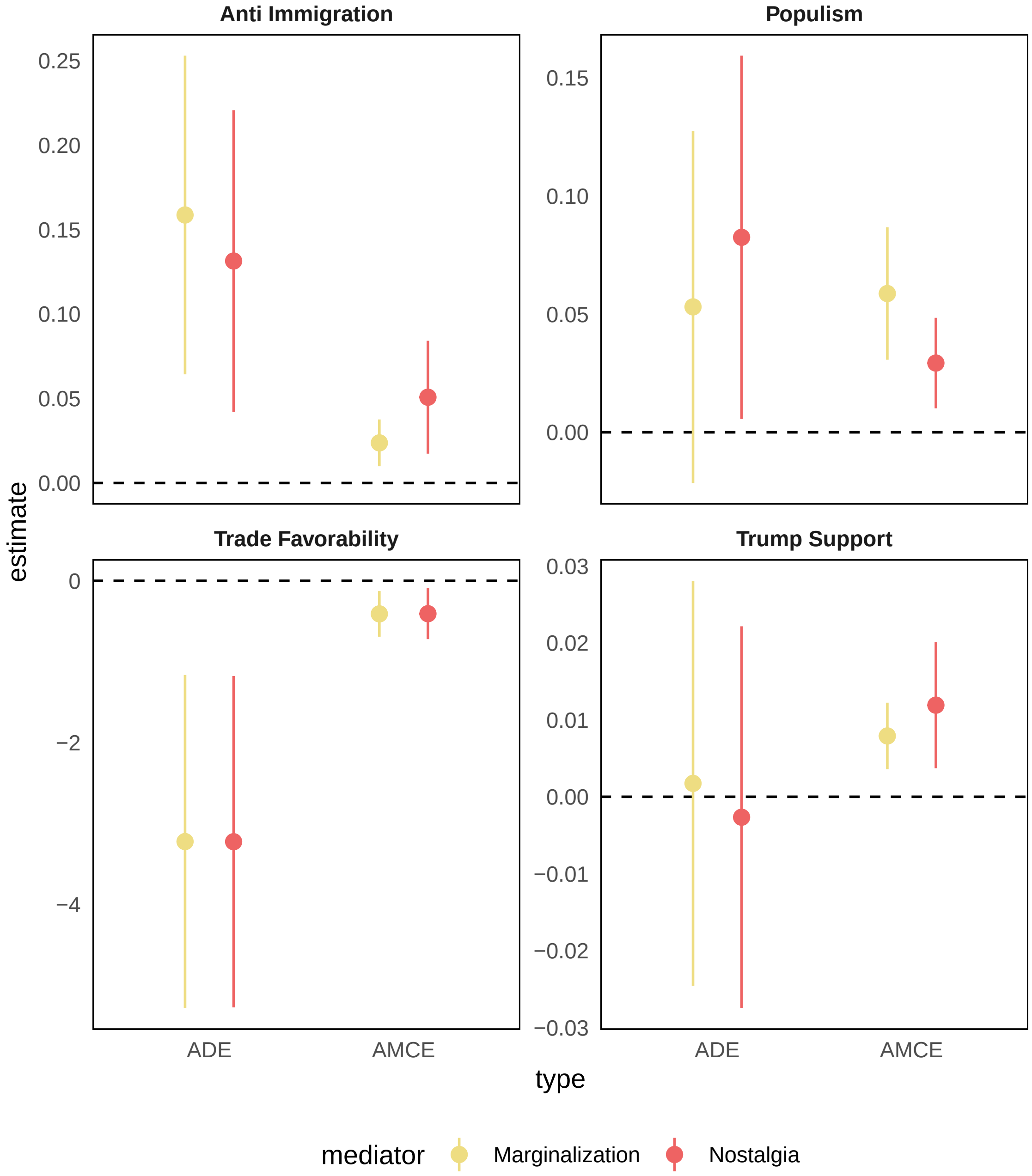


Figure C.16: Estimates of Causal Mechanisms

Similar results emerge when examining the outcomes of anti-immigration, opposition to trade, and support for a potential candidacy of Trump in 2024. A noteworthy finding in this figure is the decrease in favorability toward trade, particularly the belief that trade is detrimental to American workers. This effect includes both mediated effects through marginalization and nostalgia, representing approximately 11% of the total effect. This result is significant as it provides evidence of the linkage between exposure to trade and preferences for trade restrictions, as identified by previous scholars. Initially, these elements may appear unrelated, but understanding nostalgia as a pathway helps to comprehend how appeals for a less globalized market and overall mercantilist ideas (e.g, “Make America Great Again) align with such preferences. Likewise, considering marginalization, given the highly politicized nature of trade during campaigns, those who feel marginalized by automation may share similar sentiments with those who perceive themselves as losers from trade, as frequently emphasized in populist speeches.

C.6.1 Sensitivity Analysis

Table C.3: Sensitivity analysis: model-based inference from the experiment.

	Robot		**AI**		**Both**	
	Nostalgia	Marginalization	Nostalgia	Marginalization	Nostalgia	Marginalization
Trump	0.5	0.3	0.5	0.3	0.5	0.3
Populism	0.2512	0.3361	0.2237	0.329	0.2371	0.3158
Anti-immigration	0.332	0.1239	0.3303	0.1506	0.3309	0.1346
Trade Favorability	-0.1136	-0.0847	-0.1426	-0.1384	-0.1334	-0.1205

D Study 2, Additional Tables

Automation and cultural grievances

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Frey & Osborne	3.505***	-2.375***	-2.315***	-1.987***	-0.717***	-0.734***
	(0.231)	(0.100)	(0.094)	(0.094)	(0.052)	(0.058)
Regional Δ robots	1.042*	-0.381**	-0.333*	-0.391**	-0.259***	-0.213**
	(0.589)	(0.168)	(0.181)	(0.155)	(0.088)	(0.096)
Education (years)	-0.057***	0.076***	0.074***	0.056***	0.008***	0.008***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age	-0.011***	-0.012***	-0.003***	-0.011***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.426***	0.052***	-0.295***	-0.038**	-0.105***	-0.080***
	(0.037)	(0.018)	(0.015)	(0.016)	(0.010)	(0.011)
Country-Year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	64440	151296	150778	151615	44674	44923
$R^2(p)$	0.175	0.162	0.116	0.136	0.294	0.134
AIC	2.7e+04	6.7e+05	6.6e+05	6.5e+05	1.2e+05	1.3e+05

Standard errors clustered by region-year in parentheses

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

Table D.4: Individual and regional exposure to automation, cultural attitudes, and vote choices.
Dependent variable: A) Support for populist radical right; B) level of agreement with immigration as better for culture, economy and life. Answers range from “Not like me at all” ($= 1$) to “Very much like me” ($= 10$). C) level of agreement with “life is getting worse” and “hard to have hope about the future.” Answers range from “Agree strongly” ($= 1$) to “Disagree strongly” ($= 5$). Source: ESS (1-7) data.

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Frey & Osborne	3.640***	-2.298***	-2.339***	-1.944***	-0.800***	-0.757***
	(0.282)	(0.111)	(0.104)	(0.107)	(0.059)	(0.063)
Regional Δ robots	-0.100	-0.408**	-0.440**	-0.506***	-0.242***	-0.117
	(0.739)	(0.174)	(0.179)	(0.151)	(0.081)	(0.125)
Education (years)	-0.064***	0.083***	0.081***	0.065***	0.014***	0.011***
	(0.008)	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)
Age	-0.012***	-0.008***	0.001	-0.006***	-0.004***	-0.007***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.404***	0.082***	-0.312***	-0.044**	-0.114***	-0.085***
	(0.044)	(0.020)	(0.017)	(0.019)	(0.011)	(0.012)
Urban	-0.087*	0.164***	0.133***	0.132***	-0.006	-0.018
	(0.053)	(0.021)	(0.022)	(0.018)	(0.016)	(0.016)
Union Member	-0.096	0.124***	0.057**	0.055***	-0.069***	-0.055***
	(0.060)	(0.021)	(0.022)	(0.019)	(0.015)	(0.014)
Unemployed	0.334**	-0.217***	-0.413***	-0.311***	-0.206***	-0.206***
	(0.145)	(0.044)	(0.042)	(0.041)	(0.034)	(0.037)
Ethnic minority	0.678***	-0.436***	-0.360***	-0.480***	0.044	0.076**
	(0.201)	(0.052)	(0.047)	(0.045)	(0.029)	(0.033)
Foreign Born	-0.326***	0.483***	0.608***	0.702***	0.083***	0.007
	(0.112)	(0.043)	(0.040)	(0.036)	(0.024)	(0.028)
Precarious emp. contract	-0.064	0.054**	0.055**	0.073***	-0.010	-0.062***
	(0.073)	(0.024)	(0.022)	(0.020)	(0.015)	(0.018)
Reg. Immigrant Exposure	0.135	2.366***	-0.066	0.720	-0.807	-1.767***
	(1.489)	(0.589)	(0.482)	(0.540)	(0.851)	(0.679)
Reg. Unemployment	8.605***	0.381	-0.364	0.635	1.762	2.027
	(3.282)	(0.971)	(0.961)	(0.901)	(1.254)	(1.289)
Country-Year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	48186	108641	108113	108561	31401	31567
$R^2(p)$	0.180	0.178	0.136	0.158	0.294	0.141
AIC	2.0e+04	4.8e+05	4.7e+05	4.6e+05	8.0e+04	8.8e+04

Standard errors clutered by region-year in parentheses

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

Table D.5: Individual and regional exposure to automation, cultural attitudes, and vote choices (with additional control variables).

Dependent variable: A) Support for populist radical right; B) level of agreement with immigration as better for culture, economy and life. Answers range from "Not like me at all" ($= 1$) to "Very much like me" ($= 10$). C) level of agreement with "life is getting worse" and "hard to have hope about the future." Answers range from "Agree strongly" ($= 1$) to "Disagree strongly" ($= 5$). Source: ESS (1-7) data.

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Sd Individual Exposure	0.857***	-0.314***	-0.332***	-0.261***	-0.144***	-0.125***
	(0.112)	(0.042)	(0.042)	(0.039)	(0.022)	(0.024)
Education (years)	-0.101***	0.116***	0.111***	0.089***	0.019***	0.020***
	(0.008)	(0.004)	(0.004)	(0.003)	(0.002)	(0.002)
Age	-0.013***	-0.009***	-0.001	-0.008***	-0.004***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.427***	0.063***	-0.285***	-0.028*	-0.102***	-0.076***
	(0.038)	(0.018)	(0.015)	(0.017)	(0.010)	(0.011)
Country-Year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	64440	151296	150778	151615	44674	44923
$R^2(p)$	0.168	0.155	0.109	0.130	0.291	0.130
AIC	2.8e+04	6.7e+05	6.7e+05	6.5e+05	1.2e+05	1.3e+05

Standard errors clustered by region-year in parentheses

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

Table D.6: Automation, cultural attitudes, and vote choices. Using alternative proxy automation. Independent variable: Standardized individual-level robot exposure proposed by (Anelli, Colantone, and Stanig, 2021). Dependent variable: A) Support for populist radical right; B) level of agreement with immigration as better for culture, economy and life. Answers range from "Not like me at all" $(= 1)$ to "Very much like me" $(= 10)$. C) level of agreement with "life is getting worse" and "hard to have hope about the future." Answers range from "Agree strongly" $(= 1)$ to "Disagree strongly" $(= 5)$. Source: ESS (1-7) data.

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Sd Individual Exposure	0.908***	-0.269***	-0.306***	-0.238***	-0.135***	-0.127***
	(0.137)	(0.045)	(0.046)	(0.042)	(0.025)	(0.026)
Education (years)	-0.111***	0.124***	0.122***	0.099***	0.027***	0.023***
	(0.008)	(0.004)	(0.004)	(0.004)	(0.003)	(0.002)
Age	-0.014***	-0.006***	0.003***	-0.004***	-0.004***	-0.006***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.413***	0.100***	-0.295***	-0.029	-0.108***	-0.079***
	(0.044)	(0.020)	(0.017)	(0.019)	(0.011)	(0.012)
Urban	-0.104*	0.169***	0.137***	0.135***	-0.008	-0.019
	(0.055)	(0.021)	(0.023)	(0.018)	(0.016)	(0.016)
Union Member	-0.113*	0.138***	0.070***	0.066***	-0.065***	-0.051***
	(0.065)	(0.023)	(0.023)	(0.020)	(0.015)	(0.015)
Unemployed	0.345**	-0.233***	-0.430***	-0.325***	-0.211***	-0.211***
	(0.144)	(0.044)	(0.042)	(0.041)	(0.034)	(0.038)
Ethnic minority	0.655***	-0.438***	-0.364***	-0.483***	0.040	0.073**
	(0.201)	(0.052)	(0.048)	(0.046)	(0.029)	(0.033)
Foreign Born	-0.317***	0.490***	0.615***	0.708***	0.088***	0.012
	(0.112)	(0.043)	(0.040)	(0.036)	(0.024)	(0.028)
Precarious emp. contract	-0.032	0.037	0.038*	0.059***	-0.016	-0.067***
	(0.073)	(0.024)	(0.022)	(0.020)	(0.015)	(0.018)
Reg. Immigrant Exposure	0.055	2.503***	0.088	0.861	-0.878	-1.802***
	(1.544)	(0.587)	(0.490)	(0.548)	(0.829)	(0.672)
Reg. Unemployment	9.073***	0.135	-0.618	0.402	1.759	2.024
	(3.366)	(1.007)	(0.992)	(0.926)	(1.217)	(1.254)
Country-Year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	48186	108641	108113	108561	31401	31567
$R^2(p)$	0.173	0.171	0.128	0.152	0.290	0.138
AIC	2.1e+04	4.8e+05	4.7e+05	4.6e+05	8.1e+04	8.8e+04

Standard errors clustered by region-year in parentheses

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

Table D.7: Automation, cultural attitudes, and vote choices. Using alternative proxy for automation (with additional control variables).

Independent variable: Standardized individual-level robot exposure proposed by (Anelli, Colantone, and Stanig, 2021). Dependent variable: A) Support for populist radical right; B) level of agreement with immigration as better for culture, economy and life. Answers range from "Not like me at all" ($= 1$) to "Very much like me" ($= 10$). C) level of agreement with "life is getting worse" and "hard to have hope about the future." Answers range from "Agree strongly" ($= 1$) to "Disagree strongly" ($= 5$). Source: ESS (1-7) data.

Voting behavior explained by culture and automation

	(1) Baseline	(2) Culture	(3) Imm Eco	(4) Imm Worse Life	(5) Hopeless	(6) Worse Life	(7) est7
DV: Support for Radical Right							
Frey & Osborne	3.587***	3.587***	2.829***	2.817***	2.991***	3.905***	4.100***
	(0.337)	(0.337)	(0.359)	(0.363)	(0.356)	(0.814)	(0.793)
Pro-Immigration Culture			-0.361***				
			(0.017)				
Pro-Immigration Economy				-0.343***			
				(0.019)			
Pro-Immigration General					-0.415***		
					(0.022)		
Non-Nostalgic: Life Getting Better						-0.476***	
						(0.064)	
Non-Nostalgic: Hopeful Future							-0.137***
							(0.044)
Demographics	✓	✓	✓	✓	✓	✓	✓
NU FE	✓	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓	✓
Observations	21889	21889	21675	21592	21633	8655	8696
R^2_p	0.131	0.131	0.207	0.196	0.211	0.169	0.153
AIC	1.0e+04	1.0e+04	9271.058	9383.128	9219.355	3967.830	4060.569

Standard errors clustered by region-year in parentheses

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

Table D.8: Regression estimates of the determinants on support for a radical-right party. Source: ESS (6-7).

	(1)	(2)	(3)	(4)	(5)	(6)
	Baseline	Culture	Imm Eco	Imm Worse Life	Hopeless	Worse Life
DV: Support for Radical Right						
Sd Individual Exposure	0.028^{***}	0.016^{**}	0.018^{***}	0.018^{***}	0.028^{**}	0.034^{***}
	(0.007)	(0.006)	(0.007)	(0.007)	(0.011)	(0.011)
Pro-Immigration Culture		-0.015^{***}				
		(0.001)				
Pro-Immigration Economy			-0.013^{***}			
			(0.001)			
Pro-Immigration General				-0.015^{***}		
				(0.001)		
Non-Nostalgic: Life Getting Better					-0.016^{***}	
					(0.002)	
Non-Nostalgic: Hopeful Future						-0.004^{***}
						(0.001)
Demographics	✓	✓	✓	✓	✓	✓
NU FE	✓	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓	✓
Observations	97035	94081	93716	94199	27866	27963
R^2	0.108	0.131	0.127	0.129	0.111	0.107
AIC	-3.4e+04	-3.6e+04	-3.5e+04	-3.6e+04	-1.3e+04	-1.2e+04

Standard errors in parentheses

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

Table D.9: IV Regression estimates of the impact of a one-SD increase in regional-level robot exposure on voting for a radical-right party.
Independent variable: IV comes from (Anelli, Colantone, and Stanig, 2021). Source: ESS (1-7).

Causal mediation analysis

Automation proxied as Frey & Osborne

	(1) Culture	(2) Imm Eco	(3) Imm Worse Life	(4) Hopeless	(5) Worse Life
Frey & Osborne	0.094***	0.096***	0.097***	0.117***	0.106***
	(0.015)	(0.015)	(0.016)	(0.023)	(0.021)
Demographics	✓	✓	✓	✓	✓
NU FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Observations	28810	28698	28763	14587	14551
R^2	0.109	0.106	0.110	0.097	0.102
AIC	-4.9e+03	-4.6e+03	-4.8e+03	-5.4e+03	-5.5e+03

Standard errors clustered by region-year in parentheses

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

Table D.10: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage). Source: ESS (6-7).

	(1) Culture	(2) Imm Eco	(3) Imm Worse Life	(4) Hopeless	(5) Worse Life
Frey & Osborne	0.097***	0.097***	0.099***	0.126***	0.112***
	(0.016)	(0.016)	(0.017)	(0.024)	(0.023)
Regional Δ robots	-0.088**	-0.094***	-0.079**	0.047**	0.030
	(0.037)	(0.035)	(0.038)	(0.023)	(0.023)
Education (years)	-0.001***	-0.002***	-0.002***	-0.003***	-0.003***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
Age	-0.001***	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.020***	-0.028***	-0.023***	-0.025***	-0.026***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
Urban	-0.005	-0.006	-0.008*	-0.010	-0.010*
	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)
Union Member	0.001	-0.002	-0.000	0.000	-0.000
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Unemployed	0.009	0.004	0.005	-0.000	-0.001
	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
Ethnic minority	0.026***	0.028***	0.026***	0.028**	0.028***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)
Foreign Born	-0.004	-0.003	-0.001	-0.003	-0.000
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Precarious employment contract	-0.005	-0.005	-0.003	-0.003	-0.005
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
Regional Immigrant Exposure	-0.018	-0.045	-0.019	-0.039	-0.167
	(0.184)	(0.187)	(0.180)	(0.123)	(0.141)
Regional Unemployment	-0.158	-0.244	-0.229	0.237	0.285
	(0.257)	(0.270)	(0.256)	(0.162)	(0.175)
NU FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Observations	21863	21763	21791	10540	10505
R^2	0.112	0.109	0.112	0.091	0.098
AIC	-2.4e+03	-2.3e+03	-2.4e+03	-2.7e+03	-2.8e+03

Standard errors clustered by region-year in parentheses

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

Table D.11: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage, with additional control variables).
Source: ESS (6-7).

Automation proxied as Anelli, et al

	(1) Culture	(2) Imm Eco	(3) Imm Worse Life	(4) Hopeless	(5) Worse Life
Individual Exposure	0.499**	0.510**	0.576***	0.448*	0.840***
	(0.206)	(0.204)	(0.214)	(0.256)	(0.214)
Demographics	✓	✓	✓	✓	✓
NU FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Observations	28810	28698	28763	14587	14603
R^2	0.108	0.105	0.109	0.094	0.092
AIC	-4.8e+03	-4.6e+03	-4.8e+03	-5.3e+03	-5.3e+03

Standard errors clustered by region-year in parentheses

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

Table D.12: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage). Source: ESS (6-7).

	(1) Culture	(2) Imm Eco	(3) Imm Worse Life	(4) Hopeless	(5) Worse Life
Individual Exposure	0.818***	0.506**	0.569**	1.032***	0.916***
	(0.208)	(0.221)	(0.230)	(0.274)	(0.259)
Age	-0.001***	-0.001***	-0.001***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Female	-0.022***	-0.030***	-0.025***	-0.028***	-0.029***
	(0.005)	(0.005)	(0.005)	(0.006)	(0.007)
Urban	-0.007	-0.006	-0.008*	-0.015**	-0.015**
	(0.005)	(0.005)	(0.005)	(0.007)	(0.007)
Union Member	-0.000	-0.002	-0.001	-0.004	-0.004
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Unemployed	0.011	0.005	0.005	-0.000	-0.001
	(0.010)	(0.010)	(0.010)	(0.012)	(0.011)
Ethnic minority	0.026***	0.029***	0.027***	0.027**	0.028***
	(0.009)	(0.010)	(0.009)	(0.011)	(0.011)
Foreign Born	-0.004	-0.003	-0.001	-0.003	-0.000
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)
Precarious employment contract	-0.004	-0.004	-0.002	-0.001	-0.004
	(0.006)	(0.006)	(0.006)	(0.008)	(0.009)
Regional Immigrant Exposure	0.035	0.021	0.039	-0.077	-0.201
	(0.179)	(0.181)	(0.173)	(0.173)	(0.153)
Regional Unemployment	-0.209	-0.286	-0.264	0.200	0.228
	(0.271)	(0.285)	(0.270)	(0.171)	(0.171)
NU FE	✓	✓	✓	✓	✓
Country-Year FE	✓	✓	✓	✓	✓
Observations	21863	21763	21791	10562	10528
R^2	0.109	0.108	0.111	0.081	0.089
AIC	-2.4e+03	-2.3e+03	-2.4e+03	-2.6e+03	-2.7e+03

Standard errors clustered by region-year in parentheses

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

Table D.13: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage, with additional control variables).
Source: ESS (6-7).

Sensitivity Analysis

		Support for Radical Right
		ρ
Immigration	Country's cultural life	-0.4
	Worsening economy	-0.4
	Worsening living in the country	-0.4
Nostalgia	Life is getting worse	-0.1
	Lack of hope for the future	-0.1

Table D.14: Sensitivity analyses. Estimated using the "Medsens" statistical package in Stata (Hicks and Tingley, 2011).