The Path from Automation to Right-Wing Populism

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I investigate how automation exposure affects political behavior in post-industrial societies, focusing on right-wing populism support. I examine potential causal mechanisms by exploring the interplay between economic and cultural factors. Using double randomization of treatment and mediators in a US survey experiment, 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 right-wing populism and illiberal policies. To enhance external validity, I conduct mediation analysis using observational data from European countries. The results explain why at-risk workers turn to right-wing populism, highlighting pathways through cultural grievances and illiberal policy preferences.

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The rise of automation has transformed how tasks are performed, raising widespread concerns about the future of work. Headlines such as "AI Poses Risk of Extinction"[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 technological change. Research by Acemoglu and Restrepo (2022) finds that recent technological advancements have caused 50-70% of changes in the US wage structure. Frey and Osborne (2017) forecast that automation will displace 47% of US jobs in the next two decades, leading to labor market polarization, and middle-class erosion. In this context of increasing economic polarization, we see at-risk workers turning toward radical-right populist parties and candidates (e.g., Frey, Berger, and Chen, 2017; Milner, 2021*b*; Anelli, Colantone, and Stanig, 2021). Why are these voters switching from center-left to radical-right parties and candidates?

This paper uses an innovative survey experiment and observational analysis to examine the impact of such economic shocks on support for right-wing populism and illiberal policies.[3] I theorize that the rise of right-wing populism partly stems from increased cultural grievances, including feelings of marginalization and nostalgia, exacerbated by automation's disruptive effects on labor markets since the mid-1990s.[4] One of my survey respondents illustrates the complexity of this phenomenon: "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."[5]

In the context of these increasing concerns, I argue that this economic anxiety will generate nostalgia and feelings of marginalization, which fuel right-wing populism. These emotions serve as coping mechanisms to mitigate the insecurity arising from signifi-

[1] New York Times, May 30, 2023.

[2] CNN, Mar 19, 2023

[3] I use the classic definition of illiberal policies to refer to those that restrict the international movement of goods, capital and people.

[4] For instance, the 2017 Eurobarometer found that 75% of Europeans were concerned about job losses due to robots and AI.

[5] Another example: "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."

cant structural changes in the labor market. Scholars have previously linked periods of significant economic change with nativism and feelings of existential or societal threat (Barauskaitė, Gineikienė, and Fennis, 2022; Routledge et al., 2008; Goldstein and Peters, 2014; Bukowski et al., 2017), diminished prosocial feelings (Granulo, Fuchs, and Puntoni, 2019; Festinger, 1954), outgroup hostility (Brader, Valentino, and Suhay, 2008), and nostalgia (Zhou et al., 2013). Automation is a prime example of an economic phenomenon that can generate anxiety by undermining job opportunities and stability. This disruption fosters personal and societal insecurities, especially as individuals assess their circumstances relative to others. Such insecurities often evolve into feelings of marginalization and nostalgia for the past. Consequently, vulnerable individuals harboring such attitudes are more susceptible to candidates promoting minority prejudice and nostalgic rhetoric, which is common among right-wing populists.

Why right-wing populism instead of left? When economic transformations incite cultural rather than merely material grievances, the resultant distress cannot be mitigated through compensatory measures alone. Policies designed to obstruct such changes—for instance, those that restrict foreign goods—are more attractive than those that promote adaptation. This predilection for illiberal policies, in conjunction with cultural grievances, accounts for why economically anxious individuals are increasingly gravitating towards right-wing populism rather than the left. Right-wing populists frequently adopt illiberal policy stances while simultaneously engaging in pro-worker rhetoric, such as calling for increased tariffs to restore jobs and attract at-risk workers. Moreover, they are able to address cultural grievances by focusing on feelings of marginalization, nostalgia, and anti-establishment sentiment, a message that resonates powerfully with workers impacted by structural economic changes. This highlights an important connection between economic anxiety and the emergence of right-wing populist sentiments.

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. Many works propose a *horse race* between economic and cultural explanations for the populist backlash. However, as Agnolin, Colantone, and Stanig (2024) recently demonstrated, these approaches usually involve running models with both factors, which can introduce bias if cultural factors are post-treatment. Additionally, implementing mediation analysis on observational data can threaten validity due to potential assumption violations. This paper contributes to the debate by highlighting the mediating role of cultural grievances in explaining the propensity of at-risk workers to support the radical right with a multimethod approach, including a novel, carefully designed experiment survey experiment. This double-randomization experiment, conducted in the US, involved manipulating assignment to the treatment (exposure to economic risks) and encouragement of the mediator (activation of cultural grievances). Furthermore, the analysis was complemented by applying mediation analysis to observational survey data across thirteen European countries. This multi-method approach should serve as a template for future research and help avoid dismissing the economic roots of the populist backlash under the premise of the difficulties in disentangling effects.

This paper speaks to a growing literature disentangling the crucial role of cultural grievances in catalyzing reactions to economic shocks (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; Clark, Khoban, and Zucker, 2022). My empirical approach combines mediation analysis, a critical tool widely utilized in social psychology (Pirlott and MacKinnon, 2016; Bullock and Green, 2021; Spencer, Zanna, and Fong, 2005) to shed light on 'how' and 'why' social effects manifest, and double randomization. By experimentally manipulating both treatment and mediator, we can better ensure the independence of mediators from other variables. My design also introduces a refined compliance approach that accounts for task completion. Furthermore, this study is one of the first survey experiments to focus on AI exposure, likely to displace white-collar workers, expanding beyond the typical focus on blue-collar workers' risks.

My empirical analysis yields two kinds of findings. First, it provides compelling evidence that individuals exposed to an automation treatment (featuring replacement by robots or AI) are more inclined towards illiberal policies, including reduced favorability towards trade and immigration, than those presented with a more neutral technological context. It also shows that AI, not just robot automation, can provoke cultural grievances and illiberal attitudes without AI necessarily increasing anti-immigration sentiments. This is likely because AI replaces highly skilled jobs, which are often occupied by highly skilled immigrants, differing from the roles typically filled by low-skilled immigrants (Hainmueller and Hiscox, 2007). Second, it offers empirical evidence for the interplay between economic and cultural factors.

The implications of these findings are twofold, addressing both the demand and the supply side of politics. Firstly, the current wave of technological change disproportionately impacts the middle class, a key electoral group, for example, comprising 50 percent of the workforce in the US (Kochhar and Sechopoulos, 2022). Understanding shifting political attitudes among middle-class voters is imperative because of their role in shaping party systems and sustaining democratic institutions (Lipset, 1959; Moore, 1966; Boix, 2003; Acemoglu, Acemoglu, and Robinson, 2006). Secondly, on the supply side, these findings demonstrate that automation risk exposure markedly influences people's attitudes, suggesting a significant opportunity for politicians to engage voters concerned about these matters. Instead of merely focusing on discussions about robots or AI, there is potential for political support to be garnered by promoting distributive policies[6] from an illiberal perspective, such as enacting tariffs to bring back jobs (Dai and Kustov, 2023; Neuner and Wratil, 2022). Additionally, addressing cultural grievances offers another means to appeal to at-risk voters.

The rest of this paper first contextualizes my argument within existing literature and introduces the theoretical framework. Next, it discusses the benefits of an experimental approach and details the design. To strengthen the external validity of the findings, I then include an analysis of observational survey data, further exploring how automation risk affects political behavior via cultural grievances.

Explaining Illiberal Policy Preferences and Support for Populism

Why do some groups embrace illiberal policies and radical-right populism? This question has received growing interest among scholars (Rodrik, 2018; Broz, Frieden, and Wey-

[6]I use this term to refer to policies that target benefits to a small group of individuals while distributing the costs across a large group of individuals (e.g, tariffs).

mouth, 2021; Milner, 2021*a*; Di Tella and Rodrik, 2020). Researchers initially focused on material interests (Scheve and Slaughter, 2001; O'Rourke et al., 2001; Mayda and Rodrik, 2005), arguing that those negatively impacted by economic change, driven by factors such as increased trade or technological development, would support policies to limit that change. Subsequent studies have challenged traditional theories of material interest by exploring symbolic determinants of anti-trade sentiments, such as out-group hostility and nationalism (Guisinger, 2017; Margalit, 2012; Mansfield, Mutz, and Brackbill, 2019; O'Rourke et al., 2001). These studies demonstrate that economic anxiety, for example, the fear of job loss, can change political behavior, even if these concerns never materialize (Owen and Johnston, 2017; Mansfield and Mutz, 2013; Margalit, 2012).

More recent articles have explored how cultural grievances catalyze reactions to economic shocks, influencing political behavior. Some work has identified the moderating effect of cultural values on anti-globalization and populist attitudes. For instance, Baccini and Weymouth (2021) explore the interactive effect of race (specifically white) and deindustrialization on US presidential voting patterns. Similarly, Green, Hellwig, and Fieldhouse (2022) emphasize the significance of individuals' assessments of ethnic minorities' economic situation relative to whites in predicting support for Brexit. Clark, Khoban, and Zucker (2022) analyze how gender dynamics, in particular being male, interact with deindustrialization. Other researchers have investigated the extent to which cultural values mediated the effect of economic shocks on political behavior. Ballard-Rosa, Scheve, and Jensen (2021) and Carreras, Irepoglu Carreras, and Bowler (2019) analyze the support among Leave voters in the 2016 UK Brexit referendum, examining how cultural values such as authoritarianism, anti-immigration sentiment, Euroscepticism, ethnocentrism, and nostalgia mediate the effects of economic distress. Likewise, Hays, Lim, and Spoon (2019) show how the China shock triggers xenophobic beliefs, which in turn link to support for populism.

Despite these insights, several unresolved theoretical and empirical questions remain. For instance, why do at-risk workers in developed democracies turn to right-wing populism rather than left-wing populism? This requires a better understanding of the complex interplay between economic, cultural, and psychological factors in shaping political behavior.

Moreover, although researchers have generally considered automation a more significant factor in workforce displacement than trade and offshoring since the mid-1990s, the connection between automation and its political impact remains unclear. While it is known that exposure to automation risk correlates with support for radical right candidates[7] and opposition to globalization,[8] the reasons behind this phenomenon remain under-explored. Moreover, previous work has relied on blame misattribution to explain support for illiberal policies.[9] However, misattribution cannot explain why anxious individuals do not seek compensation rather than illiberal policies or why misattribution persists even when individuals receive accurate information about the risks of automation. Furthermore, robot-driven automation differs from AI-driven automation, and our understanding of the latter's impact remains limited.

A Non-Material Pathway to Right Populism

I propose that economic shocks increase support for right-wing populism and illiberal policies partly because exposure to these shocks triggers nostalgia and marginalization—essentially, cultural grievances—which are hallmarks of right-wing populist platforms. Specifically, I argue that structural economic change from job automation directly affects political behavior by triggering feelings of dissatisfaction, anxiety, fear, and anger. These negative emotions then manifest through nostalgia—a longing for a bygone era characterized by different societal structures, often expressed as a strengthened attachment to an idealized past—and marginalization, a feeling that one's social status is under threat. These shifts in symbolic attitudes lead to support for the illiberal policies proposed by right-wing populist parties and candidates. The diagram below illustrates the non-material pathway from automation to radical right populism.

Many of my survey participants expressed feelings of marginalization. For example, one respondent wrote: "The fear of not being able to survive is the problem, not the tech," while another stated "We MUST think about the REAL PEOPLE behind these jobs who

[7] See, for instance, Frey, Berger, and Chen (2017); Owen (2019); Gingrich (2019); Im et al. (2019); Kurer (2020); Milner (2021*b*); Colantone, Ottaviano, and Stanig (2021); Anelli, Colantone, and Stanig (2021)

[8] Refer to Di Tella and Rodrik (2020); Kaihovaara and Im (2020); Wu (2022*a*,*b*); Chaudoin and Mangini (2024),

[9] See Frey (2019) and Wu (2022*a*).

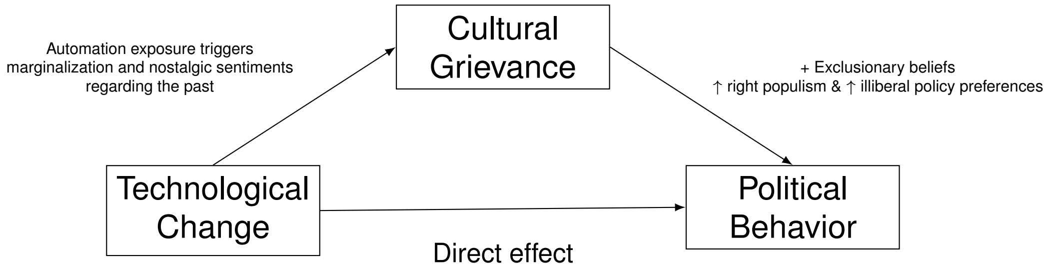

Figure 1: Mediator causality DAG

would be pushed out of the workforce. Technology is for our use, not for it to use us" (emphasis by the respondent). Such emphasis on "real people" and the feeling of being "pushed out" underscore a call to prioritize those overlooked, marginalized, and at risk of societal exclusion. This sense of exclusion is not merely about material losses but also involves a perceived erosion of recognition, akin to what scholars have identified as status threat (Mutz, 2018).

Beyond the individual and collective perceptions of marginalization, frustrations often evolve into a sense of entitlement and a belief that one deserves more recognition than members of other groups, thereby triggering support for illiberal policies, such as anti-immigration policies. Although individuals might not always pinpoint the true causes of their economic concerns,[10] they will feel marginalized and may channel these frustrations into support for more illiberal policies. Research indicates that discomfort and perceived threats can lead individuals to develop negative attitudes toward social outgroups (Allport, 1954; Glick, 2005), as a strategy to regain personal control (Bukowski et al., 2017). Specifically, within the context of technological change, Granulo, Fuchs, and Puntoni (2019) demonstrate that job security concerns can dampen prosocial feelings. Their experiments show that individuals prefer human replacements over robots when job losses affect others but prefer robot replacements when their own employment is threatened, most likely to avoid the social comparison and discomfort associated with another person taking their job.

The other mechanism through which cultural grievances link economic decline and support for illiberal policies and right-wing populism is nostalgia. Profound economic transformation, particularly change that reshapes the nature of employment relationships,[11]

[10] See Frey (2019), p. 428, and Wu (2022*a*).

[11] See Anelli, Colantone, and Stanig (2021) for further discussion.

challenges established ways of life and societal values, potentially triggering nostalgic sentiments for a secure and familiar past.[12] Research shows these emotions act as a comfort-seeking mechanism during periods of uncertainty and dissatisfaction (Davis, 1979; Hirsch, 1992; Sedikides, Wildschut, and Baden, 2004; Barauskaitė, Gineikienė, and Fennis, 2022). Furthermore, nostalgia can embody a collective dimension, often tied to an idealized "golden era" characterized by social hierarchies that favor certain demographic groups. Kojola (2019) identifies this collective nostalgia among white males in the mining industry. Similarly, Clark, Khoban, and Zucker (2022) argue that the decline of men's roles as primary earners, due to deindustrialization, may catalyze nostalgia for bygone patriarchal eras, thereby supporting more conservative political figures.

Why right-wing populism instead of left? When economic change generates cultural rather than material grievances, compensatory programs cannot address these concerns. Illiberal policies that prevent change from happening, for example, policies that restrict foreign goods, will be preferred to policies that assist adjustment to change. I argue that illiberal policy preferences and cultural grievances explain why economically anxious individuals gravitate towards right-wing populism.

Illiberal policy preferences are commonly espoused by right-wing populists, who may adopt pro-worker distributive politics rhetoric to appeal to at-risk workers (e.g., increasing tariffs to restore jobs). Additionally, they can target at-risk workers by engaging with cultural grievances, particularly by invoking feelings of marginalization and nostalgia. This dual strategy enables right-wing populists to craft messages that resonate with their intended audience. Consequently, this broadens their appeal among workers affected by structural economic changes driven by technology.

On the one hand, considering the marginalization channel, the fear of being excluded is linked to status threat and a decrease in solidarity towards those viewed as outgroups (e.g., Inglehart, 2018). Right-wing populists often provide solace to those feeling marginalized by directing blame towards foreign outgroups. This alignment with right-wing populists

[12] Recent studies link automation risk to non-economic effects: lower marriage and fertility rates, higher divorces, and increased working-age mortality from despair (Anelli, Giuntella, and Stella, 2021; O'Brien, Bair, and Venkataramani, 2022).

is not merely a matter of rhetorical proximity; recent studies have demonstrated that the success of these populists largely stems from their concrete policy positions, such as their stance against immigration and globalization (Dai and Kustov, 2023; Neuner and Wratil, 2022). Conversely, the populist left finds it challenging to propose policies that effectively address status anxiety and antipathy towards outgroups.

Right-wing populists, such as Donald Trump, who referred to threatened groups as the "forgotten workers" during his presidential campaign,[13] or Giorgia Meloni, with her emphasis on prioritizing Italian citizens over foreigners,[14] exemplify the successful appeal to marginalized individuals. The coalition between Meloni's party and Matteo Salvini's League, known for its xenophobic rhetoric, further illustrates this strategy (Mcginnis, 2021).

Nostalgia, on the other hand, fosters a longing for past societal hierarchies and values, resonating deeply with the populist right's evocation of a glorified past (e.g, van Prooijen et al., 2022). This sentiment supports radical right-wing ideologies focused on nostalgic deprivation and societal pessimism (e.g., Steenvoorden and Harteveld, 2018; Gest, Reny, and Mayer, 2018; de Vries and Hoffmann, 2018). Right-wing candidates, unlike their leftist counterparts, comfortably capitalize on this conservatism and pro-status quo sentiment, for instance, by forming nostalgic coalitions that appeal to past patriarchal and racially homogeneous societies (Kojola, 2019; Clark, Khoban, and Zucker, 2022).

There are several examples of right-wing candidates romanticizing the past, such as Donald Trump and his well-known slogan "Make America Great Again" and Boris Johnson, who evoked a sense of Britain's former power. This nostalgic appeal was particularly evident in the slogans "let's take back control," "BeLeave in Britain again," and "we want our country back" used by political right during the Brexit campaign.[15] These slogans all revolve around an idealized past, seeking to strengthen social bonds among those who long for these bygone times.

The Role of Technological Change. There are many kinds of labor market shocks that could, in theory, foster feelings of nostalgia and marginalization among voters. However, technological shocks are particularly important for two reasons. First, the middle class

[13]Rally in Dimondale, August 2016.

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

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

plays an important stabilizing role when it comes to party systems, and production automation uniquely threatens a broad array of middle-class workers (e.g., Kurer and Palier, 2019; Jaimovich and Siu, 2019). For example, tax filing software now replaces jobs traditionally filled by accountants, and autonomous vehicles threaten the livelihood of truck drivers. Even sectors requiring higher education levels are vulnerable; advancements in machine learning and AI tools, such as Google Translator and ChatGPT, may supplant tasks performed by translators, research assistants, and office clerks. Second, typically, the effects of technological shocks are irreversible, unlike, for instance, weather-induced supply shocks. A survey respondent's comment highlights the importance of dealing with worries caused by the fast growth of technology today: "I am a front-end developer and designer. Technology is always evolving in this space, but until recently, I hadn't been 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."

Operationalizing the Argument. I offer three testable hypotheses on how individuals' exposure to automation risks affects their political behavior. First, I suggest that those exposed to automation will be more likely to support illiberal policies and right-wing populism. As explained above, this hypothesis refers to a potential direct link between this economic phenomenon and politics.

Hypothesis 1. ***Populism and Illiberal Policies***: *Individuals who are exposed to automation risk are more likely to support illiberal policies and right-populist candidates.*

Second, I expect that the exposure to automation risks trigger cultural grievances, as previously described, in particular feelings of marginalization and nostalgia.

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:

Hypothesis 3. ***Mediated Effect***: *The effect of exposure to automation risk on support for right populism and illiberal policies 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 experimental and observational data. My conceptual framework focuses on the consequences of automation shocks and the mediating role of cultural grievances. It states that this exposure to automation risk triggers feelings of marginalization and nostalgia for the past. Subsequently, these sentiments contribute to the support for illiberal policies and the politicians who promote them.

Study 1: Experimental Evidence

Survey experiments provide advantages when examining the impact of economic threats on individuals' attitudes and their inclination toward supporting right-wing 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 subjects' exposure to risks affects perceptions of nostalgia and marginalization, my experiment offers distinct strengths in shedding light on the causal pathways under investigation.

To date, only a limited number of studies have utilized survey experiments to explore the effects of job automation on individuals' attitudes. For instance, 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.

I build on and advance previous experiments in several ways. First, unlike previous political science studies that focus on comparing various threat sources, my survey contrasts technology in a neutral context with technology leading to job losses, directly addressing the consequences of technological job replacement. Second, I introduce variations in the treatment to analyze the effects of incorporating robots, which predominantly affect blue-collar workers, and integrating AI, which primarily impacts white-collar workers. This approach provides new insights into the recent surge in AI's impact, an aspect previously overlooked due to an exclusive focus on manufacturing job losses. Third, I incorporate additional outcomes of interest, such as cultural grievances, to gain a comprehensive understanding of the consequences stemming from exposure to automation risk. Fourth, I implement active participation tasks and create an ecologically valid news consumption experience within the experiment rather than just prompting subjects. Lastly, my experiment is designed not only to examine the presence or absence of changes in political behavior due to automation risk but also to illuminate the mechanisms behind these changes.

Experimental Design and Procedures. I fielded the survey in the United States using CloudResearch 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).[16,17] I implement a design-based experimental mediation analysis with double randomization of the treatment (exposure to automation risk) and encouragement of mediators (marginalization and nostalgia).[18] This produces two tracks. In the first track, the treatment (exposure to automation risk) is randomly assigned, generating a pure treatment and pure control group, but there is no manipulation of the mediators (marginalization and nostalgia). In the second track, I randomize the treatment (automation), splitting the

[16] I registered the study with Open Science Framework (OSF) after a pilot.

[17] I implemented several measures to ensure data quality, including CAPTCHA to prevent spam and bots, location screening to limit participation to the US, 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% survey approval HITS on CloudResearch and pass two attention checks.

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

sample into treatment and control groups. Then, each group is randomly assigned to a marginalization or nostalgia mediator encouragement.

I adopted and modified the tasks for respondents based on a study conducted by Lelkes and Westwood (2017). In this task, respondents were presented with two news articles[19] 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 by automation, focusing on either manufacturing jobs or white-collar jobs affected by AI. 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 contrast, the control condition featured two news articles related to technological advancements in a more neutral context. 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 cultural grievances, I stimulate subjects' feelings of nostalgia or marginalization by asking them to complete a short writing exercise (autobiographical emotional memory task). The framing of this

[19]The news resembled the content that can be found in publications such as the *New York Times*. They were adapted from previous works such as Mutz (2021) and Chaudoin and Mangini (2024).

exercise was that the news organization was 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 defined nostalgia, while those in the marginalization condition were prompted to recount an instance when they (or those similar to them) felt excluded or underappreciated by those who were different. 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.[20]

After completing these tasks (reading and writing), participants were asked which article they would endorse for the organization's online news platform and whether they 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.[21]

In the post-treatment section of the survey, I asked about respondents' political attitudes, public policy preferences, subjective exposure to risk, and cultural grievances. Specifically, I aim to assess whether the automation of jobs influences political behavior, such as support for right-wing populism and illiberal policies, 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.

[20] 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).

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

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 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 examine 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.[22]

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 A.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 frequently identify treatment-outcome relationships but often overlook the mechanisms at play.[23] Mediation analysis has risen as a pivotal method to address this gap, unpacking the 'how' and 'why' behind social effects;[24] this method constitutes my primary empirical strategy. Using Baron and Kenny's (1986)

[22]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).

[23]This challenge is known as the 'black box' of causality. See Spencer, Zanna, and Fong (2005); Brady and Collier (2010); Imai et al. (2011)

[24]Editors of top social psychology journals stress identifying mechanisms, as seen in the method's adoption: 59% of JPSP and 65% of PSPB articles from 2005-2009 used it, with 55 JPSP papers in 2019 also applying the method (Pirlott and MacKinnon, 2016).

framework, this study posits that an intervention's effect (exposure to automation risk, X) on an outcome (political behavior, Y) is mediated by an intermediary (cultural grievances, M). Employing a structural equation model (equations 1-3), where i indexes subjects, α denotes intercepts, and ϵ represents zero-mean error terms from unobserved variables, this approach quantifies the total effect (ATE) of X on Y as c (equation 2), the direct effect (ADE) as d, and the mediated effect (ACME) through the product-of-coefficients method between the effects of X on M and M on Y (ab).

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

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

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

The common approach to mediation analysis, known as *measurement-of-mediation* or model-based mediation, involves the observed mediator using equation 1, instead of manipulating it (Spencer, Zanna, and Fong, 2005). Despite its prevalence, the assumptions underlying this method may be violated, for example, when unobserved confounders between M and Y can create a correlation between the error terms ϵ_1 and ϵ_3 (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.[25]

In my *design-based experimental analysis*, I tackle this issue by experimentally manipulating both the treatment and the mediator. This approach allows for unbiased estimation of b and ensures temporal precedence from X to M and from M to Y (Pirlott and MacKinnon, 2016; Bullock, Green, and Ha, 2010). Initially, I estimate the total effect (equation 2), based on the expected outcome differences between treatment and control condi-

[25]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), and Hays, Lim, and Spoon (2019), as well as studies involving randomized treatment assignment in Tomz and Weeks (2020), Powers and Renshon (2023), and Young (2019).

tions. I conduct regressions for each outcome of interest—indicators of illiberal policy preferences and right-wing populism—against the treatments. Subsequently, I regress the mediator—cultural grievances (nostalgia and marginalization)—against the treatments, establishing the effects of exposure to automation risk on the mediators (equation 1). In the third step, I estimate the impact of the mediator on political attitudes, comparing those assigned and not assigned to the encouragement task. I also re-estimate this effect using intent-to-treat (ITT) analysis, employing random assignment as an instrumental variable to mitigate endogenous compliance concerns with the encouragement task. Finally, after estimating the treatment effects on the mediator (X to M) and the mediator's effect on the outcome (M to Y), I calculate the causal mediation effect as the product of these coefficients. For a detailed discussion on the motivation, assumptions, and challenges associated with implementing causal mediation analysis, please refer to Appendix C.

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

The overall effect of exposure to automation on various political outcomes, as shown in Figure 2, aligns with my theoretical expectations. This comparison involves individuals exposed to news articles about job automation—specifically impacting manufacturing workers replaced by machines (labeled as robots) or white-collar professionals replaces by AI (labeled as AI)—versus those who read neutral articles on technological development. All estimates include pre-treatment control variables, such as gender, race, occupation (using the routine task intensity index, RTI), income, and education levels.

Figure 2 reveals that exposure to news about automation risk heightens illiberal policy preferences, which is evident from increased opposition to trade and immigration—the latter effect is specific to the robots treatment.[26] In terms of explicit support for Trump, which reflects right-wing populism, the estimate is positive; however, the evidence is insufficient to reject the null hypothesis of no relationship. These null total effects could stem from the presence of counteracting mechanisms that cancel each other out. Finally, the robots concern outcome indicates that news about job automation effectively raises concerns about automation (manipulation check).

[26] These findings are consistent with prior research that noted a rise in tariff demands (Mutz, 2021; Wu, 2022*b*).

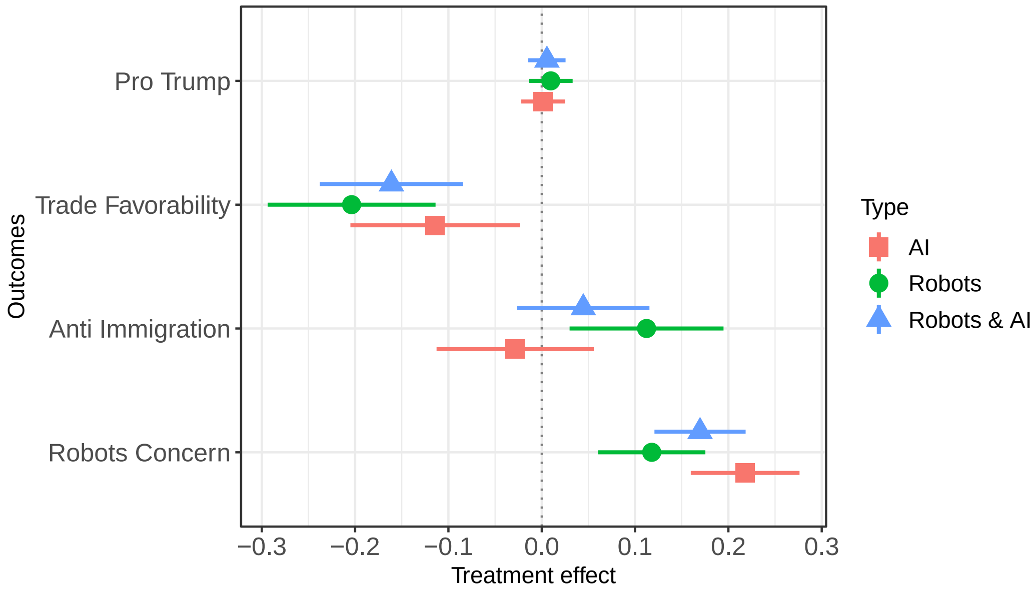

Figure 2: Total Effect of Exposure to Automation Risk (proxied as robots and AI).
Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related displacement (N=2,177), and 'Robots & AI' pools the data (N=3,133). Each row in the figure shows a set of results for a given outcome in a given treatment, distinguished by colors and shapes. Outcomes include 'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (views on trade benefits for US workers), 'Anti-immigration' (preferences on legal immigration levels), and 'Robots concerns' (perceptions of automation risks), with 'Pro Trump' binary coded and others on a 1-5 scale. Full models for the coefficients in this table are available in Table B.3-Table B.6. Appendix Figure B.1 presents estimation using Matching. See supplementary material for the exact wording.

Overall, these results support **Hypothesis 1**, linking automation risk exposure to illiberal policy preferences, though they do not provide definitive evidence with respect to the political support for Trump.[27] Nonetheless, the findings suggest that workers vulnerable to economic displacement might be predisposed to back right-wing populist candidates, who are more inclined to promote illiberal policies. For instance, Trump's advocacy for distributive policies aimed at providing targeted support to at-risk workers ("bringing jobs back") while imposing wider societal costs (for example, tariffs).

Regarding the different treatment conditions, exposing subjects to news affecting blue-collar (robot treatment) or white-collar (AI treatment) workers yields similar results across all outcomes, except for anti-immigration attitudes, which do not increase with the AI treatment. One potential explanation for the weaker effects of the AI treatment could be that workers perceive AI displacement as less likely compared to robot-induced displacement. Alternatively, subjects may link robot displacement with competition from low-skilled immigrants for remaining jobs, in contrast to AI displacement, which they might

[27] Appendix Appendix B indicates that taxing automation risk has no change, while anti-elitism sentiment increases with exposure to automation risk news.

see as related to high-skilled immigrants, hence provoking less anti-immigration sentiment consistent with previous work by Hainmueller and Hiscox (2007).

Evidence for the effect of Exposure to Automation Risk on Mediators

Turning to **Hypothesis 2**, exposure to news about automation risk increases the likelihood of scoring high on the feelings of marginalization, resulting in a change of about 23 percentage points (pp, see Figure 3). Moreover, exposure to news about technology-induced job loss has a significant impact on high levels of nostalgia, around 25 pp. Hence, exposure to these news increases cultural grievances, combining all questions about marginalization and nostalgia, by over 36 pp. These findings align with Hypothesis 2, suggesting that economic changes influence both policy preferences, like trade restrictions, and cultural grievances.

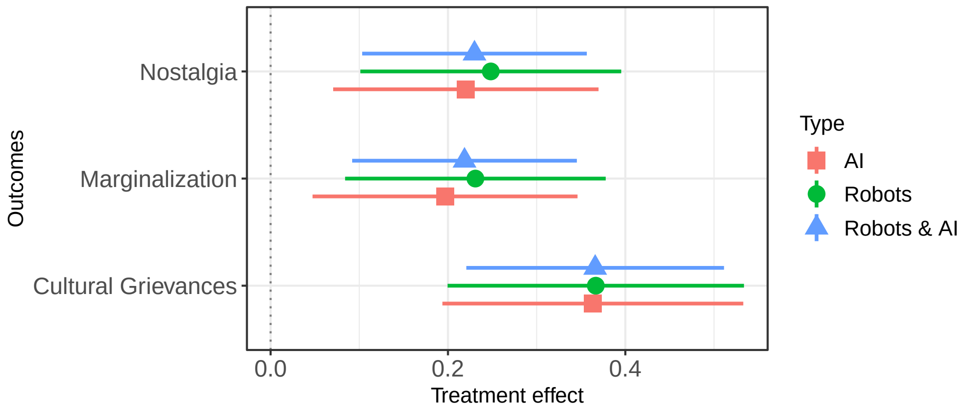

Figure 3: Treatment Effects of Exposure to Automation Risk on mediators.
Note: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related displacement (N=2,177), and 'Robots & AI' pools the data (N=3,133). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes feelings of exclusion, and 'Cultural Grievances' merges both indices. Detailed models (Table D.7-Table D.9) and estimations using Matching (Figure D.3) and full index (Figure D.2) are in the Appendix. See supplementary material for the exact wording.

Evidence for Causal Mechanisms

The effects of the encouragement task on political attitudes. So far, I have shown that exposure to news about job-threatening technological changes triggers cultural grievances and affects policy preferences. Next, I explore whether cultural grievances account for the increased support for the illiberal policies aligned with the right-wing populists' agenda. To assess the causal mediation, my experimental design not only manipulates the treatment but also includes the encouragement of the mediators.[28] I estimate the impact of the mediator encouragement (writing task about nostalgia or marginalization) on political attitudes, comparing those assigned to encouragement against those who were not. Since my focus is on the cultural grievances path, participants prompted to write about either nostalgia or marginalization are collectively considered as having been encouraged.

Moreover, to address potential endogenous compliance with the encouragement task, Figure 4 presents the estimated effect using intent-to-treat (ITT) analysis, with random assignment serving as an instrument for compliance.[29] Compliers are defined as those with high mediator levels who also completed the writing task.[30] Task completion assessment relied on hand coders labeling each response as 'complier' or 'non-complier' based on the encouragement prompt's fulfillment.[31]

Figure 4 demonstrates that the mediator increases support for Trump (right-wing populism) by approximately 10 pp among those encouraged. These findings illuminate a specific pathway from the treatment to right-wing populism, which remains hidden in the total effect estimate. Additionally, the results indicate an increase in support for illiberal policies among the encouraged group. 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 13 and 11 pp, respectively, for those randomly

[28] I use the term "encouragement" because it is not possible to directly assign respondents' feelings. Therefore, some respondents may receive the encouragement but not alter their feelings as anticipated, posing a challenge in terms of compliance. See Imai, Tingley, and Yamamoto (2013) for further discussion.

[29] Nonparametric bounds are also employed, though they provide limited information without additional assumptions about the causal structure. A detailed discussion on bounds is available in Appendix D.5.

[30] Respondents are classified as having high mediator levels if they exhibit at least a 70% probability (i.e., t=1.036) of their observed cultural grievance level under encouragement greater than the expected level in comparable groups by education, gender, and race among those without encouragement. Appendix D.4.1 discusses this method and its consistent results across various probability thresholds. Additionally, using a simplified definition of high mediator levels as above the sample median also yields consistent results (see D.4.3).

[31] Only considering hand coders provides similar results (Appendix D.4.4). Moreover, an automated measure of compliance based on word count, assessing texts exceeding the median or other thresholds like the 75th and 25th percentiles, gives consistent results, as well as, merging manual coding with word count (Appendix D.4.2).

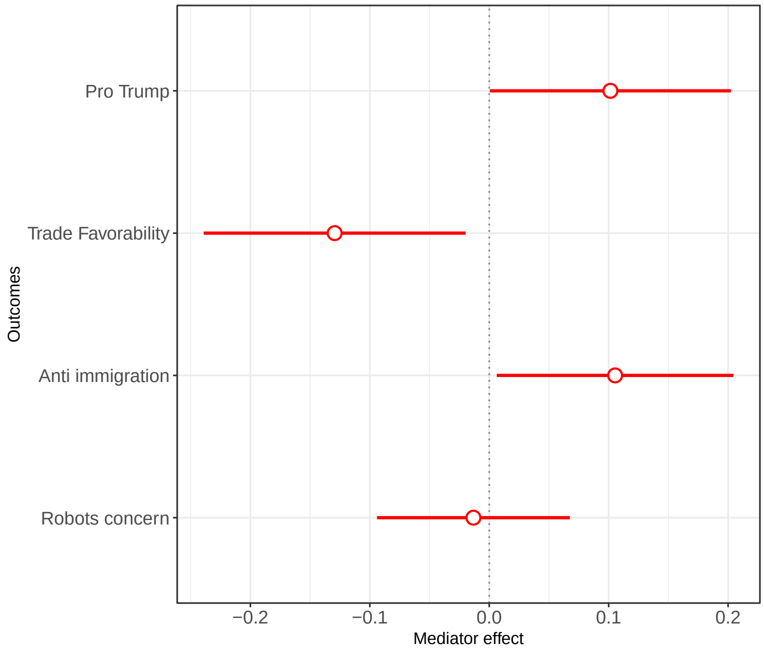

Figure 4: Mediator Effects on Outcomes, ITT
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0). Comprehensive models can be found in Table D.10, with OLS and Matching estimations presented in Appendix Figures D.4 and D.5. The supplementary material includes precise wording.

encouraged. Overall, these results show that the mediator encouragement affects political outcomes.

The mediated effect. Finally, I calculate the causal mediation effect as the product of the coefficients: the treatment effect on the mediator (cultural grievances, Figure 3) and the mediator's effect on the outcome (Figure 4). For standard error estimation, I employ the Delta Method (detailed in Appendix D.6). The mediated effect leads to an approximate 3.7 pp increase in support for Trump, a 3.9 pp rise in anti-immigration attitudes, and a 4.7-point drop in trade favorability (see Figure D.17), significant at the 90% confidence level. To contextualize these findings, I focus on changes in illiberal policy preferences. The mediated effect constitutes approximately 35% of the total change in anti-immigration attitudes and 26% of the overall decrease in trade favorability.[32] These findings support **Hypothesis** 3, which posits the existence of a mediated path through which automation influences political attitudes.[33]

[32]The results are robust to alternative definitions of compliance (refer to Appendix D.6).

[33]Additionally, the results are consistent when applying model-based mediation analysis over the survey, analyzing cultural grievance proxies directly rather the random encouragement of the mediator. For more on these findings and their robustness against the sequential ignorability assumption, see Appendix D.7.

These results show that negative economic shocks, such as those resulting from job automation trigger cultural grievances, specifically feelings of nostalgia and marginalization. These grievances, in turn, are linked with illiberal policy preferences, such as trade protectionism. The findings clarify why at-risk workers gravitate toward right-wing rather than left-wing populism, as cultural grievances heighten support for illiberal policies and politicians like Trump. However, it is crucial to acknowledge that identifying cultural grievances as a mediating factor does not preclude the possibility of other explanatory mechanisms, presenting a fruitful avenue for future research.

Study 2: Observational Cross-Sectional Evidence

In this section, I show suggestive evidence that the mechanisms uncovered in the 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.[34] 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.[35] 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

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

[35] The independent variable uses the International Standard Classification of Occupations (ISCO), harmonized to the 2010 Standard Occupational Classification (SOC) per Thewissen and Rueda (2019).

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 individual automation exposure measure, predicting probabilities based on individual attributes and occupational risk prior to the recent wave of production automation.

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 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 focusing on cultural threats, economic impacts, and overall societal effects of immigration (e.g., Hays, Lim, and Spoon, 2019; Carreras, Irepoglu Carreras, and Bowler, 2019). Responses are measured on an 11-point scale, where 0 indicates negative perceptions (e.g., immigration harms the country's cultural life) and 10 represents positive views (e.g., immigration benefits the economy). To proxy nostalgia, I use two questions: one on hope for the world's future and another on perceptions of life worsening in the country, with responses from (1) "strongly agree" to (5) "strongly disagree," available for 2006 and 2012. Although these questions imperfectly capture nostalgia, skewing towards collective pessimism, they have been used in prior research (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 examine the effects of automation risk on cultural grievances, I employ causal mediation analysis, adapting the approach from the experimental section to observational data. The primary challenge here is the potential violation of the sequential ignorability assumption (Imai et al., 2011; Keele, Tingley, and Yamamoto, 2015). This assumption requires the treatment (automation) to be independent of both the outcome and the mediator, given pretreatment covariates such as gender, and the mediator (cultural grievances) to be independent of outcomes, conditional on the treatment and covariates. To address this, I: i) include multiple pretreatment confounders (gender, age, education) and regional (NUT2 level) and country-year factors in the model; ii) use the sensitivity analysis proposed by Imai et al. (2011) to assess how deviations from sequential ignorability might influence the results.

Observational Evidence for Causal Mechanisms

I start with preliminary regressions, as detailed in Table 1, to examine the total effect of automation risk on right-wing populism and its connection with cultural grievances as mediators. These findings align with my theoretical expectations, supporting **Hypotheses** 1 and 2. Column 1 reveals that exposure to automation risk significantly increases the likelihood of supporting radical right parties. Columns 2 to 4 demonstrate that greater exposure to automation risk correlates with lower tolerance toward immigrants, indicating increased feelings of marginalization. Columns 5 and 6 illustrate that a higher probability of job computerization is linked with diminished optimism about the future, thus increasing nostalgia.[36]

	Political Behavior (Hyp. I)	Marginalization (Hyp. II)			Nostalgia (Hyp. II)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Computerization risk	3.560***	-2.355***	-2.301***	-1.964***	-0.717***	-0.742***
	(0.234)	(0.099)	(0.093)	(0.093)	(0.052)	(0.059)
Demographic	✓	✓	✓	✓	✓	✓
Country-year FE	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	63,136	150,245	149,680	150,516	44,326	44,571
R^2 (p)	0.178	0.166	0.120	0.143	0.294	0.134
AIC	2.6e+04	6.7e+05	6.6e+05	6.4e+05	1.1e+05	1.2e+05

Standard errors clustered by region-year in parentheses

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

Table 1: Effects of Exposure to Computerization Risk on Support for Right-wing populism and Cultural Grievances.

Note: This table examines the influence of automation exposure, following Frey and Osborne (2017), on right-wing populism support (1), immigration views (2-4), and future outlook (5-6). It utilizes a binary measure for populism support and scales responses from 0 (not agree) to 10 (fully agree) for immigration and 1 (strongly agree) to 5 (strongly disagree) for future sentiments. Data is from ESS rounds 1-7, with full model details in Table E.12.

[36] Appendix E.2 presents several robustness checks.

Subsequently, I turn to mediation analysis. Figure 5 and Figure 6 present results consistent with both my theory and experimental findings regarding the average causal mediation effect (ACME) and average direct effect (ADE), respectively. 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 relationship, leading to the rejection of the null hypothesis of no relationship. This lends support to **Hypothesis 3**.

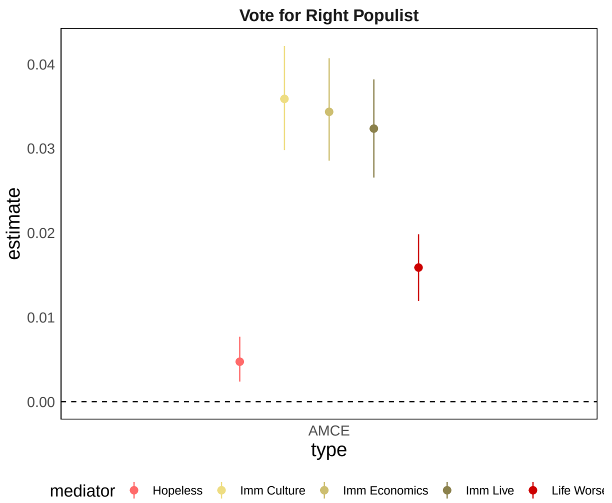

Figure 5: Mediated effect of automation through cultural beliefs on political behavior.

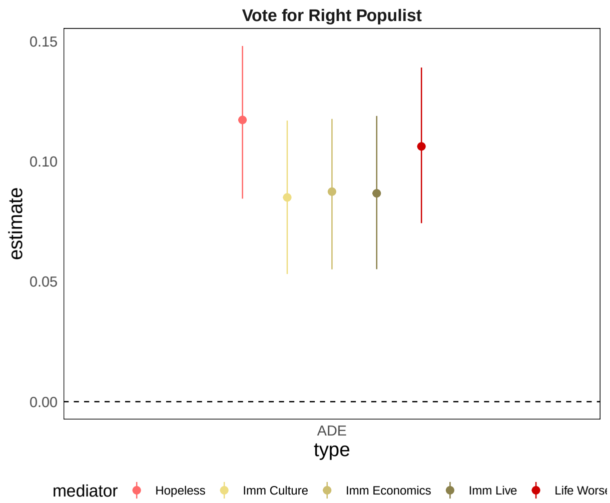

Figure 6: Direct effect of automation on political behavior.

Note: These figures show mediation analysis results on how automation exposure (following, Frey and Osborne, 2017) affects support for right-wing populism (dummy outcome) through marginalization, with immigration views (yellow) and nostalgia (future outlook, red) as mediators. Response scales for immigration range from 0 (disagree) to 10 (agree), and for future sentiments from 1 (strongly agree) to 5 (strongly disagree). Immigration: Culture (N=28,690), Economy (N=28,576), Live (N=28,638); Nostalgia: Life worse (N=14,531), Hopeless (N=14,496). Data from ESS rounds 6-7. Full results in Table E.19 and Table E.20.

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

As a robustness check, I estimate 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 E.22-E.24 in the Appendix present the results of the second stage of the mediated models. Results remain unchanged for all the model specifications.

Appendix Table E.21 presents the sensitivity of the results 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 mediator and outcome variables. If the explanatory power of the omitted confounders surpasses all the included variables, the mediated effect would become indistinguishable from zero. While such a scenario is possible, it seems unlikely.

Summary of Results

The studies reveal that exposure to automation risk significantly alters political attitudes, leading to an overall increase in illiberal preferences. These shifts can be partly attributed to automation risk evoking feelings of marginalization and nostalgia, thereby heightening cultural grievances. This mechanism is closely associated with right-wing populism. These patterns, consistent across experimental and observational research, underscore a critical challenge for democracy: individuals facing such risks tend to support parties favoring exclusionary policies, posing a threat to democratic institutions.

Conclusion

This article offers a theoretical framework and empirical evidence to elucidate the interplay between economics and culture in explaining the rise of right-wing populism. Utilizing a multimethod approach that integrates a novel survey experiment with observational cross-sectional analysis, the findings demonstrate that exposure to automation risk heightens the propensity to support illiberal policies, such as anti-globalization, that are often linked with right-wing populism. Moreover, a key mechanism behind these illiberal policy preferences is how economic shocks influence perceptions of marginalization and nostalgia, subsequently shaping political attitudes.

Ultimately, this research helps us understand why threatened workers gravitate towards right-wing populist parties and candidates. Firstly, exposure to automation risks appears to foster illiberal policy preferences commonly endorsed by right-wing populists. Secondly, such exposure also influences symbolic attitudes, leading to cultural grievances and support for candidates like Trump. These findings have important implications for the supply side of politics, indicating that politicians can target these at-risk workers through distributive politics that carry illiberal overtones, such as the imposition of higher import tariffs, and by appealing to their sense of nostalgia and perceived marginalization. A particularly strategic advantage for these leaders arises when the perceived cultural threat and distributive policies synergistically reinforce each other, as seen in Trump's tariff proposals against China.

There is still much work to be done in exploring the role of technological change and the mechanisms explaining changes in political behavior. This study limited its analysis to a single pathway—cultural grievances, with a focus on two specific operationalizations: marginalization and nostalgia. Future research should broaden this analysis to include additional mechanisms, as well as other manifestations of cultural grievances. Additionally, investigating heterogeneous treatment effects by considering pre-existing conditions such as race, class perception, and income levels would be valuable. Moreover, a deeper investigation into the effects of emerging technologies, particularly AI, would offer critical insights.

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 through survey experiments. It underscores the importance of examining overall effects carefully to uncover obscured relationships. 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. Future studies could explore alternative tasks for encouragement and compliance assessment, broadening the methodological toolkit for political science research.

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Contents

A SURVEY

A.1 Pre-Registration

The paper was pre-registered in OSF. Reference eliminated for anonymity (attached pdf as supplementary material for reviewers).

A.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 A.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 A.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).

A.3 Emotions evoked by the treatments

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.

B Average Total Effect

B.1 ATE, refers to model in Figure 2

	Dependent variable:				
	Pro Taxing Rich	Anti Elitism	Pro Trump	Trade Favorability	Anti Immigration
	(1)	(2)	(3)	(4)	(5)
Treat Robots	0.048	0.110**	0.010	−0.204***	0.112**
	(0.045)	(0.043)	(0.015)	(0.056)	(0.052)
Female	0.190***	0.132***	−0.007	−0.230***	0.089*
	(0.045)	(0.044)	(0.015)	(0.057)	(0.052)
White	−0.034	−0.077	0.038**	−0.125**	0.086
	(0.049)	(0.048)	(0.016)	(0.062)	(0.057)
Education: highschool	−0.503	0.103	0.201	0.097	0.308
	(0.397)	(0.385)	(0.130)	(0.501)	(0.459)
Education: incomplete college	−0.394	0.119	0.124	0.055	0.061
	(0.394)	(0.383)	(0.130)	(0.498)	(0.456)
Education: technical	−0.436	0.192	0.135	0.172	0.130
	(0.396)	(0.385)	(0.130)	(0.500)	(0.459)
Education: college	−0.462	−0.042	0.105	0.205	−0.077
	(0.394)	(0.382)	(0.129)	(0.497)	(0.456)
Education: gradschool	−0.464	−0.115	0.075	0.420	−0.278
	(0.396)	(0.385)	(0.130)	(0.500)	(0.459)
Education: other	−2.347***	−0.941	0.289	0.111	−0.451
	(0.649)	(0.630)	(0.213)	(0.820)	(0.752)
RTI	0.0002	0.008**	0.002	−0.003	0.007*
	(0.004)	(0.003)	(0.001)	(0.004)	(0.004)
Income dummy	Yes	Yes	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes	Yes	Yes
Observations	2,177	2,174	2,177	2,177	2,177
R^2	0.038	0.033	0.023	0.029	0.031
Note:					*p<0.1; **p<0.05; ***p<0.01

Table B.3: ATE Robots treatment, contains models of Figure 2

Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'Robots' treatment related to machine-related displacement (N=2,177) . Outcomes include 'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (views on trade benefits for US workers), 'Anti-immigration' (preferences on legal immigration levels), with 'Pro Trump' binary coded and others on a 1-5 scale.

	Dependent variable:				
	Pro Taxing Rich	Anti Elitism	Pro Trump	Trade Favorability	Anti Immigration
	(1)	(2)	(3)	(4)	(5)
Treat AI	0.002	0.056	0.002	−0.114**	−0.028
	(0.047)	(0.044)	(0.015)	(0.057)	(0.053)
Female	0.178***	0.053	−0.002	−0.168***	0.063
	(0.048)	(0.045)	(0.015)	(0.057)	(0.053)
White	−0.033	−0.026	0.041**	−0.178***	0.218***
	(0.053)	(0.049)	(0.016)	(0.063)	(0.059)
Education: highschool	−0.493	−0.312	0.066	−0.524	−0.349
	(0.390)	(0.366)	(0.121)	(0.469)	(0.435)
Education: incomplete college	−0.456	−0.126	−0.001	−0.577	−0.479
	(0.387)	(0.363)	(0.120)	(0.465)	(0.432)
Education: technical	−0.443	−0.228	0.030	−0.507	−0.314
	(0.389)	(0.365)	(0.121)	(0.468)	(0.434)
Education: college	−0.420	−0.299	−0.028	−0.359	−0.661
	(0.385)	(0.362)	(0.120)	(0.463)	(0.430)
Education: gradschool	−0.363	−0.379	−0.065	−0.261	−0.881**
	(0.388)	(0.364)	(0.121)	(0.467)	(0.433)
Education: other	−1.035*	−0.524	0.205	0.088	−1.098*
	(0.585)	(0.549)	(0.182)	(0.704)	(0.652)
RTI	−0.001	0.009***	0.001	−0.001	0.004
	(0.004)	(0.003)	(0.001)	(0.004)	(0.004)
Income dummy	Yes	Yes	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes	Yes	Yes
Observations	2,138	2,135	2,138	2,138	2,138
R^2	0.025	0.020	0.023	0.021	0.034
Note:					*p<0.1; **p<0.05; ***p<0.01

Table B.4: ATE AI treatment, contains models of Figure 2

Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'AI' treatment related to AI-related displacement (N=2,138) . Outcomes include 'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (views on trade benefits for US workers), and 'Anti-immigration' (preferences on legal immigration levels), with 'Pro Trump' binary coded and others on a 1-5 scale.

	Dependent variable:				
	Pro Taxing Rich	Anti Elitism	Pro Trump	Trade Favorability	Anti Immigration
	(1)	(2)	(3)	(4)	(5)
Treat Both	0.027	0.087**	0.006	−0.161***	0.045
	(0.039)	(0.037)	(0.012)	(0.048)	(0.044)
Female	0.174***	0.093**	−0.001	−0.182***	0.070
	(0.038)	(0.036)	(0.012)	(0.047)	(0.044)
White	−0.033	−0.027	0.039***	−0.166***	0.147***
	(0.042)	(0.040)	(0.013)	(0.051)	(0.048)
Education: highschool	−0.465	−0.193	0.103	−0.159	−0.321
	(0.324)	(0.307)	(0.104)	(0.399)	(0.368)
Education: incomplete college	−0.380	−0.096	0.035	−0.158	−0.536
	(0.321)	(0.305)	(0.103)	(0.396)	(0.365)
Education: technical	−0.416	−0.134	0.071	−0.137	−0.379
	(0.322)	(0.306)	(0.103)	(0.397)	(0.367)
Education: college	−0.405	−0.286	0.011	−0.002	−0.683*
	(0.320)	(0.304)	(0.103)	(0.395)	(0.364)
Education: gradschool	−0.388	−0.366	−0.024	0.141	−0.888**
	(0.322)	(0.306)	(0.103)	(0.397)	(0.367)
Education: other	−1.326***	−0.714	0.166	0.062	−1.193**
	(0.490)	(0.465)	(0.157)	(0.604)	(0.558)
RTI	−0.0002	0.007**	0.001	−0.001	0.004
	(0.003)	(0.003)	(0.001)	(0.004)	(0.003)
Income dummy	Yes	Yes	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes	Yes	Yes
Observations	3,133	3,129	3,133	3,133	3,133
R^2	0.025	0.021	0.019	0.022	0.030

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.5: ATE Both treatments, contains models of Figure 2

Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'Robots & AI' treatments pooling both machine and AI-related displacement (N=3,133) . Outcomes include 'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (views on trade benefits for US workers), and 'Anti-immigration' (preferences on legal immigration levels), with 'Pro Trump' binary coded and others on a 1-5 scale.

	Dependent variable:		
	Robot concerns	Robot concerns	Robot concerns
	(1)	(2)	(3)
Treat Both	0.170***		
	(0.031)		
Treat Robots		0.118***	
		(0.036)	
Treat AI			0.218***
			(0.036)
Female	−0.137***	−0.140***	−0.110***
	(0.030)	(0.036)	(0.037)
White	−0.098***	−0.126***	−0.081**
	(0.033)	(0.040)	(0.041)
RTI	0.013***	0.012***	0.014***
	(0.002)	(0.003)	(0.003)
Education dummy	Yes	Yes	Yes
Income dummy	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes
Observations	3,103	2,158	2,113
R^2	0.062	0.064	0.070

Note: *p<0.1; **p<0.05; ***p<0.01

Table B.6: ATE Manipulation checks, contains models of Figure 2

Note: This table shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related displacement (N=2,177), and 'Robots & AI' pools the data (N=3,133). Each column in the table shows 'Robot concerns'as the dependent variable. It refers to the perceptions of automation risks on a 1-5 scale, and represents a manipulation check.

B.2 ATE using Matching

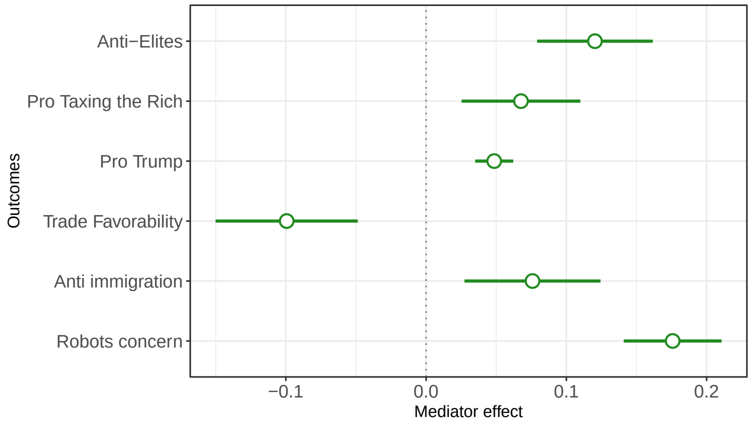

Figure B.1: Total Effect of Exposure to Automation Risk (proxied as robots and AI), using Matching.
Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. The treatments robots & AI have been pooled (N=3,133). Each row in the figure shows a set of results for a given outcome in a given treatment, distinguished by colors and shapes. Outcomes include 'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (views on trade benefits for US workers), 'Anti-immigration' (preferences on legal immigration levels), and 'Robots concerns' (perceptions of automation risks), with 'Pro Trump' binary coded and others on a 1-5 scale.

C Discussing Causal Mediation Analysis

C.1 Challenges

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 OLS and 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 and evaluating the compliance with the prompt and the intensity. 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.[37]

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

[37] 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.

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 D.6 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.

C.2 Summary

Although the recognition of the importance of causal mechanisms has been growing, the political science domain lags behind fields like social psychology in this regard. While studies focusing on mechanisms do exist, they predominantly rely on model-based inference (measurement-of-mediation-design), either using purely observational analyses (e.g, Karpowitz, Mendelberg, and Shaker, 2012; Hays, Lim, and Spoon, 2019) or by randomizing only the treatment (Tomz and Weeks, 2020; Powers and Renshon, 2023; Young, 2019). In contrast, my research introduces a design-based analysis with randomization of the treatment and encouragement of the mediator. I have integrated the parallel encouragement design and adopted various recommendations to navigate the inherent challenges of these analyses:

1. I encouraged the specific mediators towards precise writing tasks, a method well-established in prior psychological studies.
2. To account for non-compliance post-mediator encouragement, I utilized the Intent-to-Treat (ITT) approach, defining compliance indicators based on the extent of task completion and levels of the mediator. Notably, to my awareness, no prior research has integrated task completion into the compliance framework.
3. To prevent misconstruing the mediator as a moderator, I included a manipulation check for the mediators. I then scrutinized the outcomes using both the design-based and model-based approaches (i.e., measurement of mediators).
4. For potential heterogeneity effects, I meticulously delineated the conditions under which the findings are reliable, expressly identifying monotonicity as a foundational assumption.

While this research is not free of assumptions, every observational and experimental analysis carries implicit assumptions that often go unexamined. My design, in contrast, candidly discusses its assumptions, ensuring transparency throughout.

D Study 1, Causal Mediation Analysis Details

D.1 Effects of T on M, refers to model in Figure 3

Following are the tables related to the main text figures.

	Dependent variable:		
	Nostalgia	Marginalization	Cultural Grievances
	(1)	(2)	(3)
Treat Robots	0.248***	0.231**	0.367***
	(0.092)	(0.092)	(0.104)
Female	−0.044	0.030	−0.031
	(0.093)	(0.093)	(0.106)
White	0.092	−0.291***	−0.064
	(0.102)	(0.100)	(0.115)
Education: highschool	−0.506	−1.082	−0.934
	(0.783)	(0.859)	(0.789)
Education: incomplete college	−0.891	−1.394	−1.239
	(0.778)	(0.855)	(0.784)
Education: technical	−0.703	−1.004	−1.089
	(0.782)	(0.858)	(0.788)
Education: college	−1.107	−1.340	−1.505*
	(0.777)	(0.854)	(0.783)
Education: gradschool	−0.991	−1.221	−1.329*
	(0.783)	(0.859)	(0.790)
Education: other	−1.186	−2.160	−1.375
	(1.397)	(1.445)	(1.405)
RTI	0.013*	0.013*	0.021**
	(0.007)	(0.007)	(0.008)
Income dummy	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes
Observations	2,177	2,177	2,177
Log Likelihood	−1,377.356	−1,377.210	−1,136.916
Note:			*p<0.1; **p<0.05; ***p<0.01

Table D.7: Effects of Treatment-Robots on Mediators, contains models of Figure 3

Note: This table shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. The treatment is 'Robots' for machine-related displacement (N=2,177). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes feelings of exclusion, and 'Cultural Grievances' merges both indices.

	Dependent variable:		
	Nostalgia	Marginalization	Cultural Grievances
	(1)	(2)	(3)
Treat AI	0.220**	0.197**	0.363***
	(0.094)	(0.093)	(0.106)
Female	0.036	0.048	−0.042
	(0.094)	(0.094)	(0.107)
White	0.041	−0.287***	0.032
	(0.105)	(0.103)	(0.119)
Education: highschool	−0.217	−1.046	−1.393*
	(0.728)	(0.757)	(0.760)
Education: incomplete college	−0.414	−0.997	−1.621**
	(0.722)	(0.750)	(0.753)
Education: technical	−0.347	−0.658	−1.388*
	(0.726)	(0.753)	(0.756)
Education: college	−0.776	−0.953	−1.743**
	(0.720)	(0.747)	(0.750)
Education: gradschool	−0.807	−0.867	−1.862**
	(0.726)	(0.753)	(0.758)
Education: other	−1.587	−0.555	−2.108
	(1.316)	(1.114)	(1.330)
RTI	0.005	0.002	0.002
	(0.007)	(0.007)	(0.008)
Income dummy	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes
Observations	2,138	2,138	2,138
Log Likelihood	−1,345.605	−1,345.092	−1,111.423
Note:			*p<0.1; **p<0.05; ***p<0.01

Table D.8: Effects of Treatment-AI on Mediators, contains models of Figure 3

Note: This table shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. The treatment is 'AI' for AI-related displacement (N=2,138). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes feelings of exclusion, and 'Cultural Grievances' merges both indices.

	Dependent variable:		
	Nostalgia	Marginalization	Cultural Grievances
	(1)	(2)	(3)
Treat Robots & AI	0.230***	0.219***	0.366***
	(0.079)	(0.079)	(0.091)
Female	0.009	0.028	−0.019
	(0.077)	(0.077)	(0.087)
White	0.091	−0.301***	−0.009
	(0.085)	(0.083)	(0.095)
Education: highschool	−0.787	−1.205*	−1.250*
	(0.641)	(0.696)	(0.646)
Education: incomplete college	−1.022	−1.331*	−1.475**
	(0.636)	(0.692)	(0.642)
Education: technical	−0.917	−0.984	−1.329**
	(0.639)	(0.694)	(0.644)
Education: college	−1.335**	−1.349*	−1.729***
	(0.635)	(0.690)	(0.640)
Education: gradschool	−1.257**	−1.242*	−1.671***
	(0.639)	(0.694)	(0.646)
Education: other	−1.593	−0.927	−1.592
	(1.036)	(0.992)	(1.040)
RTI	0.010*	0.009	0.010
	(0.006)	(0.006)	(0.007)
Income dummy	Yes	Yes	Yes
Encouragement dummy	Yes	Yes	Yes
Observations	3,133	3,133	3,133
Log Likelihood	−1,997.818	−1,993.138	−1,673.287
Note:			*p<0.1; **p<0.05; ***p<0.01

Table D.9: Effects of Treatment-Both on Mediators, contains models of Figure 3

Note: This table shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. The treatment is 'Robots & AI' for pooled machines and AI-related displacement treatment (N=3,133). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes feelings of exclusion, and 'Cultural Grievances' merges both indices.

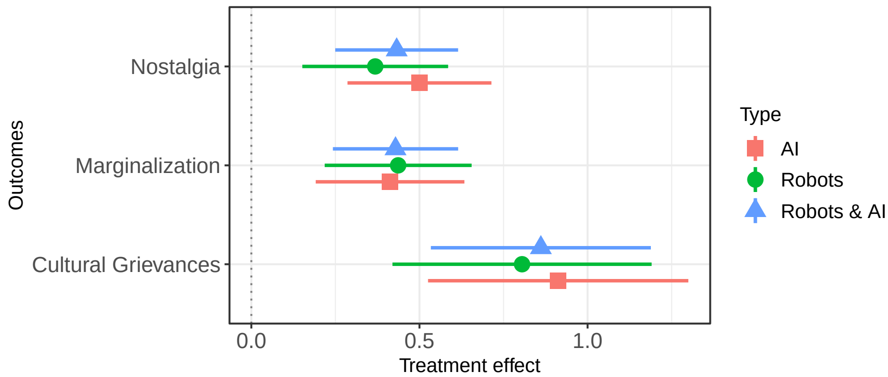

Figure D.2: Treatment Effects of Exposure to Automation Risk on mediators. *Note*: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related displacement (N=2,177), and 'Robots & AI' pools the data (N=3,133). Results for each mediator are shown, with the full indices, derived from the sum of various questions, resulting in a range of 3 to 15 for marginalization and nostalgia, and cultural grievances is the addition of these two indices.

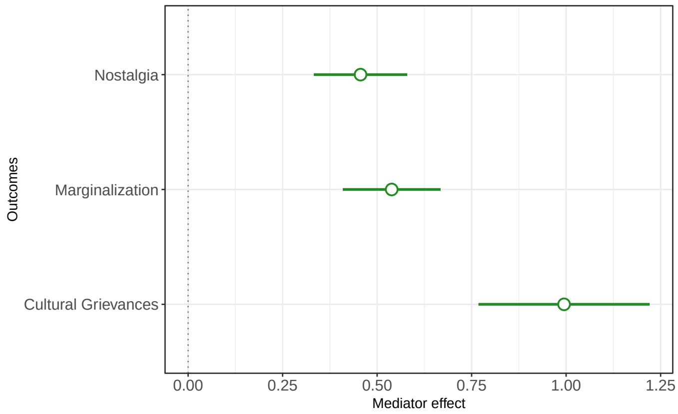

Figure D.3: Treatment Effects of Exposure to Automation Risk on mediators, using Matching. *Note*: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. Treatments were pooled 'Robots & AI' (N=3,133). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes feelings of exclusion, and 'Cultural Grievances' merges both indices.

D.2 Effects of M on Y, refers to Figure 4

	Dependent variable:			
	Pro Trump	Trade Favorability	Anti Immigration	Robots Concern
	(1)	(2)	(3)	(4)
Mediator Encouraged	0.102*	−0.130*	0.107*	−0.013
	(0.061)	(0.067)	(0.060)	(0.049)
Female	−0.022	−0.123***	0.026	0.014
	(0.016)	(0.018)	(0.016)	(0.013)
White	0.086	0.017	−0.084	−0.033
	(0.139)	(0.151)	(0.136)	(0.111)
Education: highschool	0.029	0.071	−0.132	−0.031
	(0.138)	(0.150)	(0.135)	(0.110)
Education: incomplete college	0.032	0.076	−0.108	−0.032
	(0.138)	(0.150)	(0.136)	(0.111)
Education: technical	−0.026	0.127	−0.204	−0.044
	(0.137)	(0.150)	(0.135)	(0.110)
Education: college	−0.031	0.173	−0.244*	−0.078
	(0.139)	(0.151)	(0.136)	(0.111)
Education: gradschool	0.235	0.031	−0.435**	−0.292*
	(0.210)	(0.228)	(0.206)	(0.168)
Education: other	0.060***	−0.059***	0.061***	0.001
	(0.018)	(0.019)	(0.018)	(0.014)
RTI	0.001	−0.0001	0.002*	−0.0002
	(0.001)	(0.001)	(0.001)	(0.001)
Income dummy	Yes	Yes	Yes	Yes
Treat dummy	Yes	Yes	Yes	Yes
Observations	3,133	3,133	3,133	3,133
R^2	0.035	0.047	0.050	0.008
Note:				*p<0.1; **p<0.05; ***p<0.01

Table D.10: ITT, contains models of Figure 4
Note: This figure represents the effects of the mediators on the outcomes of interest. The sample comprises 3,133 respondents, of whom 1,816 received encouragement, and 1,317 did not. Random assignment was the instrument for compliance. Each row in the figure shows a set of results for a given outcome in a given treatment, distinguished by colors and shapes. The outcome variables are defined as follows: 'Pro Trump' refers to the willingness to vote for Donald Trump if he runs again for president; 'Trade favorability' denotes opinions on whether increased trade with other countries has been beneficial or detrimental to American workers; 'Anti-immigration' measures attitudes towards whether the federal government should increase, decrease, or maintain the current number of legal immigrants allowed into the United States, with positive numbers indicating a preference for a decrease; 'Robots concerns' is an index that combines several questions about subjective perceptions of the risk of automation (robots or AI) and serves as a manipulation check. All outcomes were transformed into binary, coded as 1 or 0.

D.3 Effects of M on Y, alternative estimations to results in Figure 4: OLS & Matching

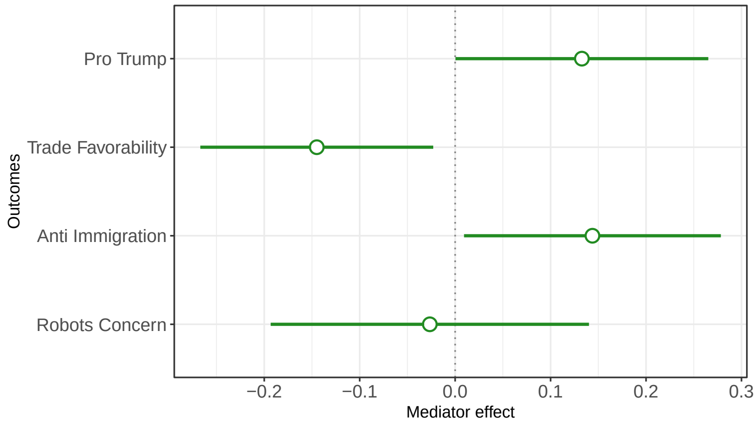

Figure D.4: Encouragement Effects on Outcomes, OLS

Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as a treatment variable and OLS, with control variables (education, race, income, RTI, gender). The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

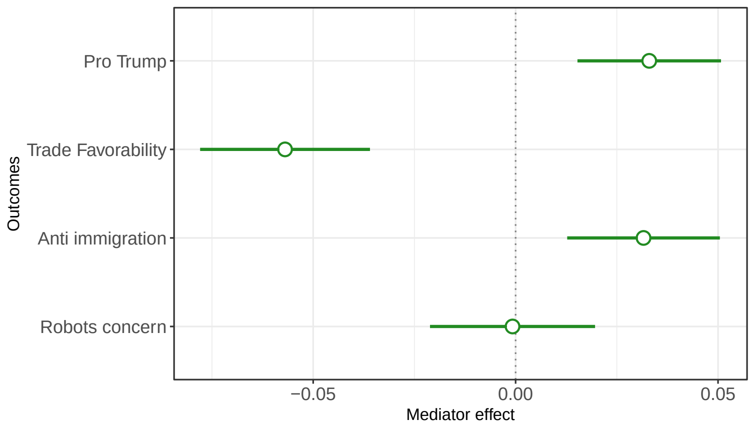

Figure D.5: Encouragement Effects on Outcomes, Using Matching

Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as a treatment variable and matching on covariates (education, race, income, RTI, gender). The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.4 Effects of M on Y, alternative definition of compliers to results in Figure 4: ITT

The following section explore alternative definitions of compliers based on: 1) how to define high level of the mediator; 2) how to identify task effort (i.e, hand coders or number of words).

D.4.1 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 D.6 shows that the results remain unchanged.

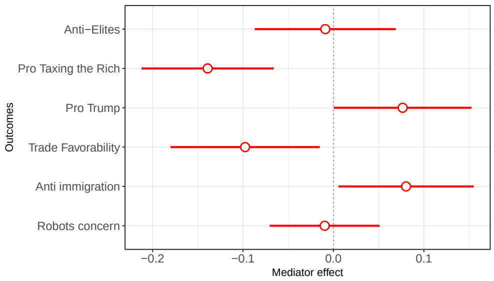

Figure D.6: T=0.842 (p-value<0.4)

Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

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 D.7-D.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.

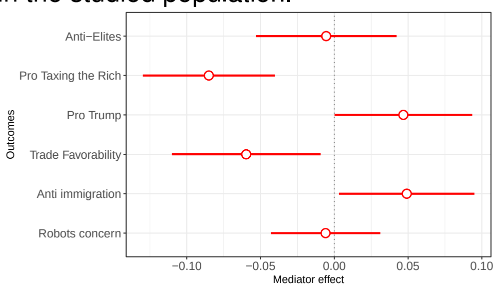

Figure D.7: T=0.18 (p-value<0.5)

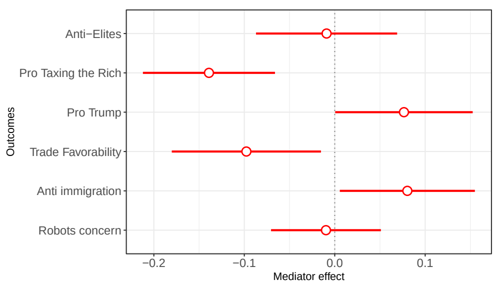

Figure D.8: T=0.842 (p-value <0.40)

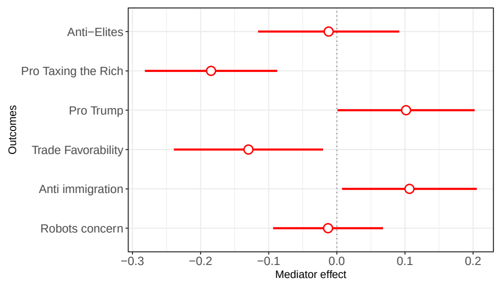

Figure D.9: T=1.036 (p-value<0.3)

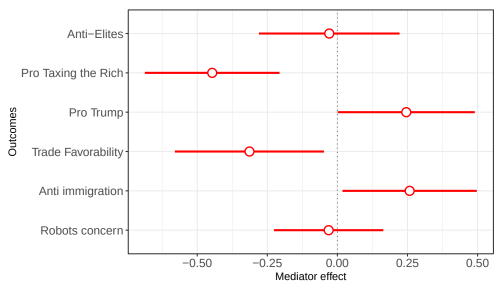

Figure D.10: T=1.646 (p-value<0.1)

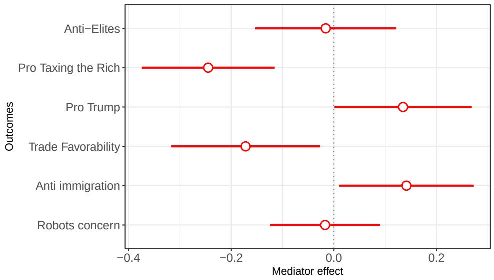

Figure D.11: T=1.282 (p-value <0.20)

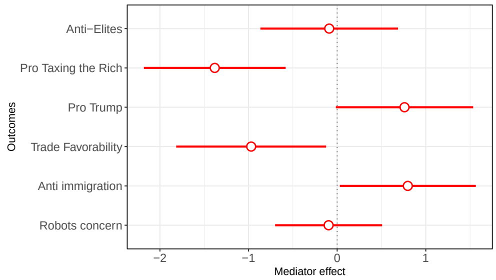

Figure D.12: T=1.962 (p-value <0.05)

Note: These figures (D.7-D.12) show the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.4.2 ITT - compliers & task efforts To estimate compliance, I have also integrated automatic 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.

ITT - compliers, task effort (hand coders + words) & high levels of the mediator (relative to non-encouraged)

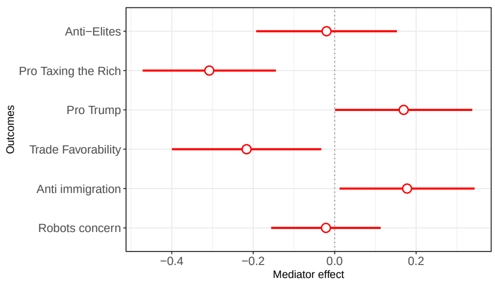

Figure D.13: Compliance defined as: 1) high levels of the mediator relative to non-encouraged (t=1.036), 2) task completion defined as hand coders and more than median words.

Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.4.3 ITT - compliers as high levels of the mediator relative to the median level in the sample. If we estimate using as the definition of high levels the median of the sample instead of comparing the non-encouraged group, the results remain the same.

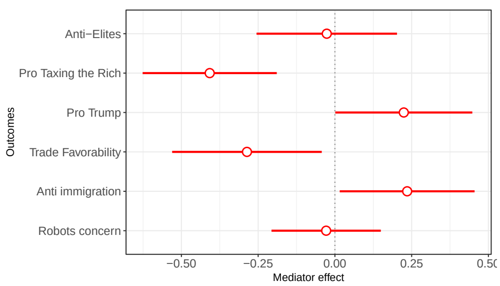

Figure D.14: High levels of the mediator as higher than the median in the sample, and hand-coders as compliers.

Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.4.4 ITT - compliers only as hand coders code as 1 (followed the prompt). If we estimate using as the definition of compiler based on whether they followed the prompt, and without considering the level of the mediator.

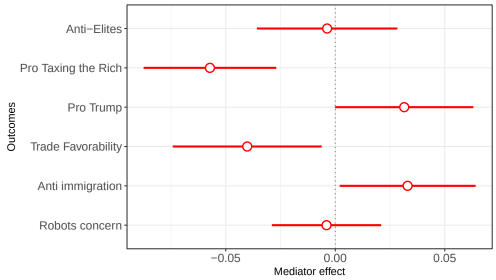

Figure D.15: Compliers only based on hand-coders annotation of the writing task.
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.5 Bounds

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

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

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

Figure D.16 presents the bounds, which are not informative.

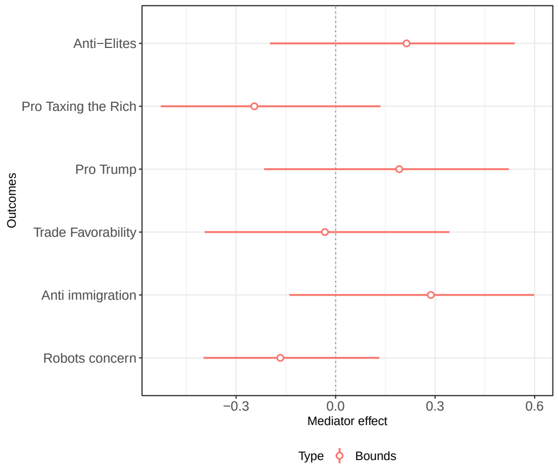

Figure D.16: Mediator Effects on Outcomes, Bounds
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not. The estimates are done using bounds. The results for each outcome—'Pro Trump' (willingness to vote for Trump), 'Trade favorability' (perceptions of trade's benefits for US workers), 'Anti-immigration' (views on immigration levels), and 'Robots concerns' (automation risk perceptions)—are detailed by row. Outcomes were binary coded (1 or 0).

D.6 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$(p_1 p_2)$

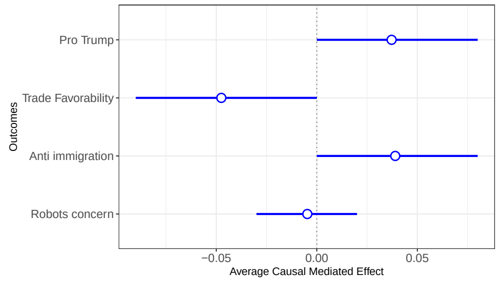

Figure D.17: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to those non-encouraged (t=1.036), and 2) task completion as hand-coders.

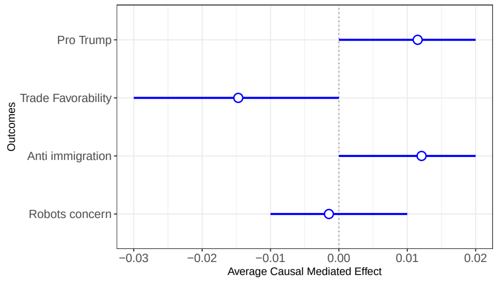

Figure D.19: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to median level in the sample, and 2) task completion as more than median words.

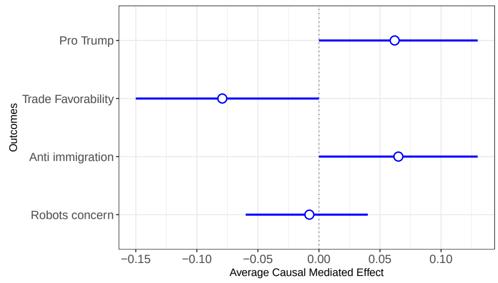

Figure D.18: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to those non-encouraged (t=1.036), and 2) task completion as hand-coders & more than median words.

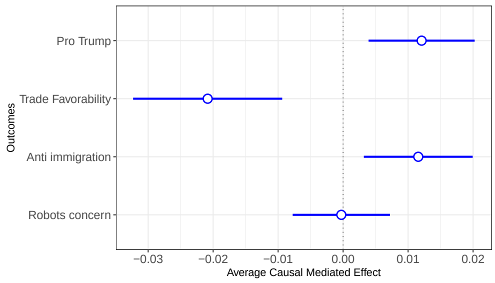

Figure D.20: Mediated effect, with the encouragement effects on outcomes estimated using Matching

Note: These figures (D.17-D.20) show the average mediated causal effect. N = 3,133, with 1,816 receiving encouragement and 1,317 not. Moreover 1,951 received either robot or AI treatment and 1,182 the control. The estimates result from the product of coefficients (from the effects of the treatment on cultural grievances) and the effects of the encouragement on the outcomes. SE comes from Delta method.

D.7 Model Base Inference with Survey Data

Figure D.21 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.

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.

D.7.1 Sensitivity Analysis

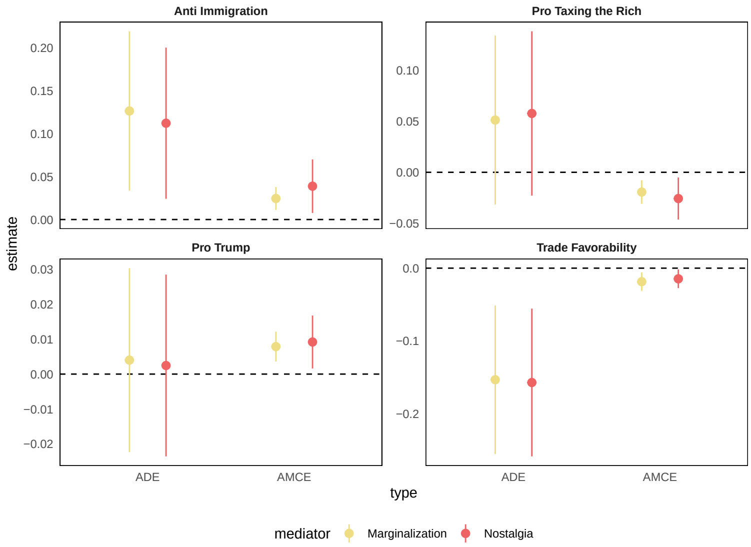

Figure D.21: Estimates of Causal Mechanisms using Survey Data
Note: These figures represent the results from the model-based mediation analysis. The treatment variable is being exposed to job-threatening displacement due to robots or AI. The outcome variables are defined as follows: 'Pro Trump' refers to the willingness to vote for Donald Trump if he runs again for president; 'Trade favorability' denotes opinions on whether increased trade with other countries has been beneficial to American workers; 'Anti-immigration' measures attitudes towards whether the federal government should increase, decrease, or maintain the current number of legal immigrants allowed into the United States, with positive numbers indicating a preference for a decrease. The mediator variables are indicators for cultural grievances and are defined as follows: 'Nostalgia' (red tones) is a dummy variable that signifies high values on the nostalgic index. This index aggregates responses to questions about feelings of sentimentality for the past and concerns over the loss of traditions. 'Marginalization' (yellow tones) is a dummy variable that represents high scores on the marginalization index, which includes questions related to concerns about people like the respondent no longer representing American identity, their values being disrespected, and feelings of being poorly treated in society, among others. Source: Survey data collected (N=3,133, pool data).

	Robot		**AI**		**Both**	
	Nostalgia	Marginalization	Nostalgia	Marginalization	Nostalgia	Marginalization
Pro Trump	0.5	0.3	0.5	0.3	0.5	0.3
Pro Taxing the Rich	-0.2458	-0.1088	-0.2573	-0.1242	-0.2503	-0.1198
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

Table D.11: Sensitivity analysis: model-based inference from the experiment.

Note: This table represents the sensitivity analysis of the results from the model-based mediation analysis on survey data. In this case, the result of the sensitivity analysis refers to each treatment. The columns associated with 'Both' are related to Figure D.21.

E Study 2, Observational Evidence for Exposure to Automation on Politics and Mediators

E.1 Refers to Table 1

Following Table 1 with control variables.

	Political Behavior (Hyp. I)	Marginalization (Hyp. II)			Nostalgia (Hyp. II)	
	(1)	(2)	(3)	(4)	(5)	(6)
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
Frey & Osborne	3.560***	-2.355***	-2.301***	-1.964***	-0.717***	-0.742***
	(0.234)	(0.099)	(0.093)	(0.093)	(0.052)	(0.059)
Education (years)	-0.057***	0.079***	0.076***	0.059***	0.009***	0.008***
	(0.007)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Age	-0.011***	-0.011***	-0.002***	-0.009***	-0.005***	-0.007***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)
Female	-0.428***	0.059***	-0.290***	-0.031*	-0.106***	-0.080***
	(0.038)	(0.017)	(0.015)	(0.016)	(0.010)	(0.011)
Ethnic minority	0.672***	-0.740***	-0.716***	-0.886***	0.007	0.079***
	(0.161)	(0.045)	(0.046)	(0.038)	(0.024)	(0.030)
Constant	-5.709***	7.427***	5.791***	6.007***	3.186***	2.955***
	(0.489)	(0.531)	(0.189)	(0.143)	(0.072)	(0.272)
Country	✓	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓	✓
Observations	63,136	150,245	149,680	150,516	44,326	44,571
R^2 (p)	0.178	0.166	0.120	0.143	0.294	0.134
AIC	2.6e+04	6.7e+05	6.6e+05	6.4e+05	1.1e+05	1.2e+05

Standard errors clustered by region-year in parentheses
$^{*}\ p < 0.1$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

Table E.12: Automation, cultural attitudes, and vote choices.
Note: This figure represents the effects of exposure to automation on the outcome of interest (support for right-wing populism) and mediators. The independent variable is exposure to automation approached following Frey, Berger, and Chen (2017) 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.

E.2 Study 2, Additional Tables: Robustness checks associated with Table 1.

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 E.13 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. (The results remain the same if I exclude employment variables, which arguably may also be post-treatment.) 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-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 E.14)

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 E.15, and E.16 (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 E.17).(Comparable models were replicated in Tables E.18, utilizing robot adoption in different countries as an instrumental variable for robot exposure (Anelli, Colantone, and Stanig, 2021). The results remained consistent.) 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.

	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 E.13: 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 clustered by region-year in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.14: 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 E.15: 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 E.16: 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

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
DV: Support for Radical Right						
Frey & Osborne	3.587***	2.829***	2.817***	2.991***	3.905***	4.100***
	(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	21675	21592	21633	8655	8696
R^2_p	0.131	0.207	0.196	0.211	0.169	0.153
AIC	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 E.17: Regression estimates of the determinants on support for a radical-right party.
Note: This table represents the effects of exposure to automation on the outcome of interest (support for right-wing populism) and mediators. These result show the relationship including the mediator as control variable as a robustness check. The independent variable is exposure to automation approached following Frey, Berger, and Chen (2017) 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 (6-7).

	Political Behavior	Immigration (Hyp. I)			Nostalgia (Hyp. II)	
	Radical Right	Culture	Economy	Live	Life Better	Hopeful
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 clustered by region-year in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.18: IV Regression estimates of the impact of a one-SD increase in regional-level robot exposure on voting for a radical-right party.
Note: This table represents the effects of exposure to automation on the outcome of interest (support for right-wing populism) and mediators. These result show the relationship including the mediator as control variable as a robustness check. The independent variable is exposure to automation approached following Anelli, Colantone, and Stanig (2021) 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).

E.3 Observational: Causal mediation analysis

E.3.1 Refers to Figure 5 & Figure 6 Automation proxied as Frey & Osborne

	(1) Culture	(2) Economy	(3) Live	(4) Hopeless	(5) Worse Life
Frey & Osborne	0.095***	0.097***	0.098***	0.117***	0.106***
	(0.016)	(0.015)	(0.016)	(0.023)	(0.021)
Education (years)	-0.001*	-0.001**	-0.001***	-0.002***	-0.002***
	(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***	-0.027***	-0.023***	-0.023***	-0.024***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)
Ethnic minority	0.026***	0.028***	0.025***	0.030***	0.029***
	(0.007)	(0.008)	(0.008)	(0.009)	(0.008)
Country-year FE	✓	✓	✓	✓	✓
NUTS FE	✓	✓	✓	✓	✓
Observations	28690	28576	28638	14531	14496
R^2	0.110	0.106	0.110	0.097	0.102
AIC	-4.8e+03	-4.5e+03	-4.7e+03	-5.3e+03	-5.4e+03

Standard errors clustered by region-year in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table E.19: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage).
Note: This table represents the Average Mediated Causal Effect (ACME) and Average Direct Effect (ADE) of exposure to automation on the outcome of interest, which is support for right-wing populism. The treatment variable, exposure to automation, is approached following Frey, Berger, and Chen (2017). The dependent variable is support for the populist radical right. The mediators include proxies for nostalgia and marginalization. For marginalization, the relevant question measures the level of agreement with the statement that immigration is beneficial for culture, economy, and life. Answers range from "Not like me at all" ($= 0$) to "Very much like me" ($= 10$). For nostalgia, it measures the level of agreement with statements such as "life is getting worse" and "it's hard to have hope for the future," with answers ranging from "Agree strongly" ($= 1$) to "Disagree strongly" ($= 5$). Source: ESS 6-7. Refers to Figure 5 & Figure 6.

Type	**Estimate**	**CI Lower**	**CI Upper**	**Mediator**
AMCE	0.036	0.030	0.042	Immigration: Culture
ADE	0.085	0.053	0.117	Immigration: Culture
Total Effect	0.121	0.090	0.153	Immigration: Culture
Proportion Mediated	29.7%	0.222	0.409	Immigration: Culture
AMCE	0.034	0.029	0.041	Immigration: Economics
ADE	0.087	0.055	0.118	Immigration: Economics
Total Effect	0.122	0.091	0.153	Immigration: Economics
Proportion Mediated	28.3%	0.212	0.400	Immigration: Economics
AMCE	0.032	0.027	0.038	Immigration: Live
ADE	0.087	0.055	0.119	Immigration: Live
Total Effect	0.119	0.087	0.150	Immigration: Live
Proportion Mediated	27.3%	0.202	0.378	Immigration: Live
AMCE	0.016	0.012	0.020	Nostalgia: Life Worse
ADE	0.106	0.074	0.139	Nostalgia: Life Worse
Total Effect	0.122	0.090	0.155	Nostalgia: Life Worse
Proportion Mediated	13.0%	0.091	0.189	Nostalgia: Life Worse
AMCE	0.005	0.002	0.008	Nostalgia: Hopeless
ADE	0.117	0.085	0.148	Nostalgia: Hopeless
Total Effect	0.122	0.091	0.153	Nostalgia: Hopeless
Proportion Mediated	3.8%	0.018	0.067	Nostalgia: Hopeless

Table E.20: Mediation Analysis
Note: This table represents the Average Mediated Causal Effect (ACME) and Average Direct Effect (ADE) of exposure to automation on the outcome of interest, which is support for right-wing populism. The treatment variable, exposure to automation, is approached following Frey, Berger, and Chen (2017). The dependent variable is support for the populist radical right. The mediators include proxies for nostalgia (indicated in red tones) and marginalization (indicated in yellow tones). For marginalization, the relevant question measures the level of agreement with the statement that immigration is beneficial for culture, economy, and life. Answers range from "Not like me at all" ($= 0$) to "Very much like me" ($= 10$). For nostalgia, it measures the level of agreement with statements such as "life is getting worse" and "it's hard to have hope for the future," with answers ranging from "Agree strongly" ($= 1$) to "Disagree strongly" ($= 5$). Source: ESS 6-7. Refers to Figure 5 & Figure 6.

E.3.2 Sensitivity Analysis associated to Figure 5 Table E.21 present 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 E.21: Sensitivity analyses. Estimated using the "Medsens" statistical package in Stata (Hicks and Tingley, 2011).
Note: This table represents the sensitivity for the ACME presented in Figure 5.

E.3.3 Robustness Check Mediation Following alternative specifications of the mediation analysis.

	(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 E.22: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage, with additional control variables). *Note*: The treatment variable, exposure to automation, is approached following Frey, Berger, and Chen (2017), regional robots exposure comes from Anelli, Colantone, and Stanig (2021). This model contains additional control variables. The dependent variable and mediators are similar to the main model. 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 E.23: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage).
Note: This table represents the Average Mediated Causal Effect (ACME) and Average Direct Effect (ADE) of exposure to automation on the outcome of interest, which is support for right-wing populism. The treatment variable, exposure to automation, is approached following Anelli, Colantone, and Stanig (2021). The dependent variable is support for the populist radical right. The mediators include proxies for nostalgia and marginalization. For marginalization, the relevant question measures the level of agreement with the statement that immigration is beneficial for culture, economy, and life. Answers range from "Not like me at all" $(= 0)$ to "Very much like me" $(= 10)$. For nostalgia, it measures the level of agreement with statements such as "life is getting worse" and "it's hard to have hope for the future," with answers ranging from "Agree strongly" $(= 1)$ to "Disagree strongly" $(= 5)$. 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 E.24: Mediated effects of Risk of automation on electoral support for the radical right (2nd stage, with additional control variables).
Note: This table represents the Average Mediated Causal Effect (ACME) and Average Direct Effect (ADE) of exposure to automation on the outcome of interest, which is support for right-wing populism. The treatment variable, exposure to automation, is approached following Anelli, Colantone, and Stanig (2021). The dependent variable is support for the populist radical right. The mediators include proxies for nostalgia and marginalization. For marginalization, the relevant question measures the level of agreement with the statement that immigration is beneficial for culture, economy, and life. Answers range from "Not like me at all" $(= 0)$ to "Very much like me" $(= 10)$. For nostalgia, it measures the level of agreement with statements such as "life is getting worse" and "it's hard to have hope for the future," with answers ranging from "Agree strongly" $(= 1)$ to "Disagree strongly" $(= 5)$. Source: ESS 6-7.

F Research Ethics

This study was reviewed and granted an exemption by the Institutional Review Board of XXX on March 16, 2023 (STUDY22120089).

Voluntary informed consent was obtained by all human subjects. It was obtained electronically and was built into the survey flow. Subjects were free to decline participation. Prior to providing consent, subjects were informed about foreseeable risks, the lack of direct benefits associated with the research, whether and how identities and data will be protected, compensation, and the voluntary nature of the study, and were provided relevant contact information from the University's IRB and researcher.

The motivation of the study was not provided at the instruction step to avoid biasing subjects' responses. There was no more than minimal harm to subjects, and at the consent step individuals were told that they would be "fully debriefed about the study's purpose and procedures after your participation is complete." At the end of the study, subjects were fully debriefed about purposes and procedures.

I worked with a survey company (CloudResearch CloudResearch (2024), and the survey was prepared using Qualtrics) that does market research and compensates survey takers.

The instruction blocks indicate:

> If you are a citizen of the United States, 18 years or older, and part of the workforce (currently working or looking for a job), we're inviting you to participate in a research study designed, among other things, to help a news organization decide what content it should feature in a news website about social change. You will be fully debriefed about the study's purpose and procedures after your participation is complete.
>
> We estimate that answering the survey will take about 15-18 minutes. We will pay participants who pass a simple attention check about basic facts of the survey $1.50 for questionnaires that are at least 90% complete. You will be given a completion code for payment. There are no direct benefits from participation. There is a minimal risk of breach of confidentiality. We are not collecting any personally identifiable information, but you will be asked your zip code in order to identify the area of the country in which you live. In addition, your participation is voluntary. You can exit the survey at any time, and you may choose not to answer sensitive questions, but you cannot withdraw from the study after submitting the questionnaire.
>
> If you are eligible and agree to participate in this survey, please click I AGREE TO PARTICIPATE below.
>
> You may contact the Human Subjects Protection Advocate of the IRB Office, XXXXXX to discuss problems, concerns, and questions; obtain information; offer input; or discuss situations in the event that the research team is unavailable. Thank you very much for your time and for considering our request

The debriefing block:

> Purpose of the Study:
>
> > This study is about attitudes toward technological change, and its consequences on political choices such as political engagement. This survey collects baseline demographic and political data and explores the effects of exposure to automation risks on support for redistribution, integration to the global economy, and voting behavior.
> >
> > In order to test the project's hypotheses, the survey asked you to help a new news website about social change, and read two news. One group, read news related to job losses, and other one about new technologies. Please note that neither the news website nor individuals or companies mentioned do not in fact exist. We apologize for the use of a fictitious article.
>
> Confidentiality:
>
> > Your responses will be kept strictly confidential. No personally identifying information has been collected during the process of the survey (e.g., name, exact address). If you have any concerns please contact the researcher, XXXX at XXX.

G Survey Questionnaire

You will find attached the survey questionnaire without the introduction block and debriefing section for anonymity.