From Automation to "Make It Great Again": The Cultural Path to Right-Wing Populism

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I examine how exposure to automation risk—from robots or AI—shapes political behavior. I argue that nostalgia for a past social order, often a coping response to perceived marginalization, is a central pathway from automation threats to politics. Using a U.S. survey experiment with double randomization of both treatment and mediator encouragement, I compare respondents exposed to neutral technological news with those shown articles on job loss from robots or AI. I then encourage cultural grievances—nostalgia or perceived marginalization—to identify causal mechanisms. Results show that automation risk heightens these grievances, which in turn increase support for right-wing populism and illiberal policies such as protectionism. To assess external validity, I replicate the analysis with observational data from 13 European countries. Across both designs, nostalgia and perceived marginalization consistently emerge as channels, indicating that compensation alone is unlikely to blunt illiberal shifts unless policymakers address underlying cultural grievances.

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

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AI and robotic technologies are reshaping work and wages. Early research links a large share of wage polarization to task-replacing technologies, with technology accounting for roughly one-half to two-thirds of recent changes in the U.S. wage structure (Acemoglu and Restrepo, 2022). Public concern mirrors these pressures.[1] Yet in many countries the main electoral movement has not backed compensation or retraining. Instead, parties that promise a return to a familiar order have advanced. Why does economic disruption travel with demands for restoration?

I argue that perceived automation risk triggers *cultural grievance*—feelings of exclusion likely cooped through nostalgia for a "better" past—and that this pathway tilts voters toward illiberal policy preferences.[2] Automation is often thought to be permanent, not cyclical, so it invites a sense of loss that appears hard to reverse. Survey respondents capture this tension in their own words: "Technology can be a blessing and a curse... I've liked what it has done for me at work, but I also know it's only a few steps away from being able to do my job," and "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."

Reducing recent political shifts to either "the economy" or "culture" is too narrow. I am not alone in this view: prior research links economic change to shifts in attitudes and voting. Economic shocks are associated with authoritarian and nativist views (Ballard-Rosa, Scheve, and Jensen, 2021; Carreras, Irepoglu Carreras, and Bowler, 2019); deindustrialization reshapes social roles in ways tied to conservative support (Clark, Khoban, and Zucker, 2024); trade-induced manufacturing decline coincides with xenophobic and populist voting (Hays, Lim, and Spoon, 2019); and economic anxiety and cultural discontent accompany populist attitudes (Rhodes-Purdy, Navarre, and Utych, 2021*a*). Psychological research points to similar mechanisms, connecting major disruptions to perceived social threat (e.g, Barauskaitė, Gineikienė, and Fennis, 2022; Routledge et al., 2008; Granulo, Fuchs, and Puntoni, 2019; Zhou et al., 2013). Disentangling the economic–cultural relationship poses a research-design challenge: if cultural attitudes lie on the causal path from economic shocks to political outcomes, controlling for them in outcome regressions risks

[1]For example, with headlines such as "AI Poses Risk of Extinction," New York Times, May 30, 2023. Moreover, before the generative-AI wave, estimates suggested that 47% of U.S. jobs faced high risk of computerization (Frey and Osborne, 2017), and a 2017 Eurobarometer wave reported that about three-quarters of respondents were worried about job losses due to robots and AI.

[2]By illiberal policies I mean restrictions on the cross-border movement of goods, capital, or people.

post-treatment bias (Agnolin, Colantone, and Stanig, 2024). Moreover, standard mediation with observational data relies on strong, often untestable, assumptions. Consequently, most studies examine only one segment of the causal chain—either the connection between economic shocks and attitudes or that between attitudes and political outcomes.

I address these design limitations using an encouragement–mediator framework that randomizes both the causal variable and the mediator. First, respondents are asked to review and rate two short news pieces for an online blog; topics are randomly assigned to either an article about automation-driven job loss—arising from manufacturing or AI displacement—or to a neutral technology story that does not mention job loss. Second, a random subset completes a brief "letter to the editor" task, prompting either a time when they felt excluded or a nostalgic recall, thereby increasing cultural grievance. This double randomization identifies the pathway from automation risk to policy views and vote intentions through grievance, following experimental causal-chain strategies in social psychology and extending them to political economy (Pirlott and MacKinnon, 2016; Bullock and Green, 2021; Spencer, Zanna, and Fong, 2005). Finally, to assess external validity, I also conduct mediation analyses using European Social Survey data from 13 countries.

The paper contributes in several ways. First, it shows that exposure to automation risk—including AI-related displacement—increases nostalgia and perceived feelings of exclusion, and links these reactions to shifts in policy and political preferences. Second, it moves beyond studies focused on industrial robots (e.g., Chaudoin and Mangini, 2024; Gallego, Kurer, and Schöll, 2021; Boix, Gonzalez-Rostani, and Owen, 2025) by examining AI risk, which is more typical among white-collar workers. Third, it centers nostalgia as a coping response to perceived marginalization, using prompts and item-based measures adapted from psychology. Finally, empirically, the double-randomization design enables causal identification of the full causal chain, offering a template for future research in political economy. The study also carefully mimics realistic news exposure through active tasks, employing a cover story to enhance ecological validity (Lelkes and Westwood, 2017; Gonzalez-Rostani and Hays, 2025), and includes a simple compliance measure based on respondents' open-ended writing to verify uptake.

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, the study provides evidence that cultural grievance transmits part of the effect of automation risk onto political outcomes: the treatments heighten nostalgia and perceived marginalization, and these in turn increase support for populist-right candidates. This mediated pathway can be masked in estimates that only target total effects.

These findings have important implications for both the demand and supply sides of politics. On the demand side, technological change weighs heavily on the middle class, a group that anchors party systems and democratic stability (Moore, 1966; Boix, 2003). If many such voters respond to perceived automation risk with cultural grievances, polarization can deepen and democratic institutions may be at risk. On the supply side, politicians can tap into this anxiety. Right-wing populists have paired pro-worker nationalism with exclusionary proposals, as seen in recent U.S. elections (González-Rostani, 2024). Beyond rhetoric about robots or AI, distributive policies that appear to "bring jobs back," such as tariffs, can be electorally attractive (Dai and Kustov, 2023; Neuner and Wratil, 2022). Policies that address grievances directly may also be effective. Meanwhile, the left has struggled to appeal to these voters as automation erodes employment in union-dense sectors (Agnolin et al., 2024), and social democratic parties have often failed to represent them, widening gaps in representation (Berman, 2021; Roberts, 2024). For policymakers, these findings imply that if the goal is to blunt illiberal movements, economic compensation alone is unlikely to suffice; cultural grievances must also be addressed.

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.

Automation, Nostalgia, and the Path to Right-Wing Populism

Economic Change and Cultural Backlash: What We Know and What Is Missing

Existing research links major economic disruptions to political backlash through both material and symbolic channels. Classic accounts emphasize material interests (Scheve and Slaughter, 2001; O'Rourke et al., 2001; Mayda and Rodrik, 2005). More recent work shows that perceptions and anxieties shape preferences even without direct losses: people react to anticipated harm or status decline, not only to realized job loss (Guisinger, 2017; Margalit, 2012; Mansfield, Mutz, and Brackbill, 2019; Owen and Johnston, 2017; Mansfield and Mutz, 2013).

In the United States, Mutz (2018) finds that a perceived loss of group standing among traditionally high-status Americans was a stronger predictor of support for Donald Trump in 2016 than personal economic hardship. This framing pits economic and cultural explanations against each other, but I contend that both are important. A growing body of research shows how threatened group status can drive support for populist and radical-right movements. Gidron and Hall (2017) argue that declining social status fosters scapegoating and a turn toward populist actors. Gest, Reny, and Mayer (2018) document that white working-class voters in the United States and United Kingdom who perceive economic deprivation are more likely to back radical-right candidates, while Kurer (2020) link realized status decline—such as job downgrading—to similar patterns of support. Steenvoorden and Harteveld (2018) show that societal pessimism, or the belief that society is in decline, correlates with greater radical-right support, and Ballard-Rosa, Scheve, and Jensen (2021) connect authoritarian predispositions to the same outcome. Other work highlights how economic change can generate changes in attitudes, as when job losses in male-dominated industries spark a "breadwinner backlash" (Clark, Khoban, and Zucker, 2024).

A few studies trace the full pathway from economic shocks, through cultural change, to political outcomes. Research on the "China shock" finds little evidence that personal economic downturn alone pushed voters toward the far right; rather, trade-induced job losses heightened xenophobic beliefs, which then increased support for populist-right parties (Hays, Lim, and Spoon, 2019). Carreras, Irepoglu Carreras, and Bowler (2019) examine Brexit and argue that long-term local economic decline fostered eurosceptic and anti-immigrant attitudes, which in turn boosted support for Leave. Similarly, Rhodes-Purdy, Navarre, and Utych (2021*a*) advance an "affective political economy" model in which economic shocks trigger negative emotions that feed cultural discontent, showing that economic anxiety and cultural discontent jointly activate populist attitudes.

Despite evidence that automation has displaced—and could continue to displace—more workers than trade and offshoring since the mid-1990s, its political impact remains understudied (Gallego and Kurer, 2022). In the economic shock literature, automation is often acknowledged as a source of displacement but grouped with other forces, and many studies mention it only in passing when discussing globalization. This leaves its distinctive political economy underdeveloped. Yet automation may provoke a different mix of fears and frustrations than an import shock or a recession, making the lack of theory and evidence on its political consequences a notable gap.

Existing research does find that higher exposure to automation—measured either by a region's adoption of robots or by an individual's risk of job automation—correlates with greater support for populism.[3] Far less is known about the mechanisms. Prominent explanations emphasize misdirected blame or nationalism. One argument is that many displaced workers do not recognize automation as the cause and instead fault more visible targets, such as immigrants (Frey, 2019; Wu, 2022*a*). Another is that automation-induced insecurity heightens nationalist sentiment (Chaudoin and Mangini, 2024). While these accounts some of the mechanisms behind the backlash, they leave puzzles: if misperception were the only driver, providing accurate information in experiments should reduce backlash—yet effects persist. Likewise, they struggle to explain why redistribution fails to ease these grievances.

[3] Studies across several advanced democracies document this pattern (Frey, Berger, and Chen, 2017; Gingrich, 2019; Im et al., 2019; Kurer, 2020; Milner, 2021; Anelli, Colantone, and Stanig, 2021; González-Rostani, 2024), and similar evidence has recently emerged in the Global South (Boix, Gonzalez-Rostani, and Owen, 2025).

From Automation Threat to "Make It Great Again"

I build on this literature to argue that the breadth and perceived irreversibility of automation make economic insecurity feel permanent. These emotions (dissatisfaction, fear, anxiety, and anger rooted in expected decline) spill into cultural grievances that standard compensatory policies cannot calm. Such grievances often appear as perceived marginalization or cultural discontent and, in turn, prompt nostalgia for an earlier social order. Through this channel, technological disruption links to right-wing populist appeals that promise restoration rather than adaptation.

Not all economic shocks have the same political effects. Automation, understood as the replacement of human labor with machines or algorithms, is a distinctly dislocating form of structural change. Two features make it especially consequential for political behavior. First, the scope of automation is unusually broad. Unlike many trade shocks that strike particular industries or primarily lower-skill jobs, automation reaches across sectors and skill levels, including the middle class. This wide field of exposure creates a diffuse anxiety that "no one is safe" from displacement. People who never expected to be near the economic margins (for example, middle-skill office workers or technicians) now worry about obsolescence. The perceived status loss across a large slice of society feeds a sense of decline.

Second, technological displacement is likely to be seen as irreversible and identity-threatening. Unlike cyclical shocks, automation is experienced as one-way change. Displaced tasks appear gone for good, with few plausible paths back to prior roles. The result is not only income loss but identity loss: craft, status, and community ties anchored in now-automatable work. This permanence encourages a sense of decline (Elchardus and Spruyt, 2016) and alienation (Gonzalez-Rostani, 2022). As one survey respondent put it, "We must think about the real people behind these jobs who would be pushed out of the workforce. Technology is for our use, not for it to use us." The sentiment captures a fear of being rendered useless by an impersonal force.

The breadth and permanence of automation's threat make its political implications distinct. These structural features do not just reshape labor markets; they reshape how people see their place in society. The response is likely to unfold along two temporal dimensions—present-focused feelings of exclusion and past-focused longings for restoration.

Perceived marginalization and cultural discontent (present-focused). Individuals come to see themselves as "forgotten" and pushed to the edges of society. Even when they cannot clearly identify automation as the cause (its effects are diffuse and hard to trace), they register a generalized threat of obsolescence. The result is a feeling of being left behind by progress and excluded from prosperity that others (urban elites, tech workers, globalized professionals) seem to enjoy.

Nostalgia (past-focused). As a coping strategy, people are likely to recall a time when work felt meaningful, community life was stable, and roles were clear. Research in psychology shows that uncertainty, such as the one that could be triggered by rapid modernization, heightens nostalgia, which in turn helps restore meaning and continuity (e.g., Zhou et al., 2013, 2022). In the automation setting, longing for the pre-automation workplace blends with longing for the status it conferred (for example, the respected blue-collar breadwinner or the proud single-industry town).

Nostalgia is a distinct and consequential element of the cultural response to automation because it brings a clear temporal contrast: a glorified yesterday against an unsatisfactory today. Political actors can convert diffuse discontent into a compelling story—"Our country was strong when you had your old jobs and traditional values; we should return to that strength." This frame offers not only blame but a positive destination, which can be powerfully mobilizing.

Why the Destination Is the Populist Right?

I argue that when economic change produces cultural grievances rather than purely material ones, people gravitate to political offerings that promise to undo the cultural change. Right-wing populists are uniquely well-positioned to capitalize on these sentiments. There are several reasons for this alignment.

First, the policy prescriptions associated with nostalgic and marginalization-driven grievances tend to be illiberal and reactionary, aiming to reverse or halt the perceived decline. When automation is blamed for massive displacement, preferred remedies aim to halt change: curb outsourcing, tighten immigration, or restrict new technologies. This turn-back-the-clock impulse appears most often on the populist right, where leaders promote protectionism and nativism, including tariffs to reclaim jobs, strict immigration laws, and opposition to environmental rules that threaten legacy industries. The appeal is the promise of restoration. Social democrats may offer unemployment insurance, retraining, or education subsidies, yet for people experiencing nostalgic loss, cash or classes rarely match the hope of recovering a familiar way of life. As a result, compensatory programs seldom address these cultural sentiments, leaving a representational gap that right-populist parties step into.

Second, right-wing populism contain this rhetorical validation. Populist right leaders often style themselves as champions of the "forgotten" people. Donald Trump's campaign famously invoked the "forgotten men and women" of America, implicitly acknowledging those who felt left behind by economic and cultural change. Similarly, European radical right figures like France's Marine Le Pen or Italy's Matteo Salvini and Giorgia Meloni emphasize that "ordinary natives" have been marginalized by globalist policies and cosmopolitan elites. This rhetoric not only recognizes the grievance – it redirects it. They frame their mission as giving voice and power back to those who have been silenced or displaced in the modern economy.

Nostalgia is also actively cultivated by the populist right. These movements and politicians present themselves as vehicles to "Make X Great Again," explicitly invoking a return to an imagined past utopia. Brexit's slogans—"Take Back Control" and "We Want Our Country Back"—urged voters to reclaim a supposedly better past, while Trump's MAGA slogan called directly for rekindling a bygone golden age. By contrast, left-wing parties tend to ground their appeals in visions of a better future through progressive reform, which does little to satisfy the nostalgic yearning of those who believe society as a whole was better decades ago. In this way, nostalgic grievance aligns more easily with the right, particularly the far right, which often promotes social conservatism, defense of traditional hierarchies, and a chauvinistic nationalism that frames returning to "how things were" as a political imperative.

In sum, automation-triggered cultural grievances tend to align with the right, where they find political resonance. Combining demands for recognition with nostalgia for a perceived better past, they match the anti-elite and traditionalist appeals of right-wing populism, which validates cultural discontent and promises to restore lost status. Left-wing actors, in contrast, struggle to make comparable appeals without undermining their progressive, inclusionary values. As a result, cultural grievances born of economic fear – when they center on loss of status and longing for the past – drive voters disproportionately into the arms of right-wing populist candidates and parties.

Operationalizing the Argument

I propose a non-material pathway from automation to politics. Automation risk heightens anxiety and powerlessness, which appear as perceived marginalization and nostalgic longing. These, in turn, increase openness to right-populist rhetoric and illiberal policy positions that promise protection and restoration.

Hypothesis 1. ***Populism and Illiberal Policies*** *Individuals exposed to higher automation risk will be more likely to support right-wing populist candidates and illiberal policies.*

Hypothesis 2. ***Cultural Grievance*** *Individuals exposed to automation risk are more likely to develop cultural grievances.*

Hypothesis 3. ***Mediated Effect*** *The effect of automation exposure on support for right-wing populism and illiberal policies is partly mediated by cultural grievances.*

Testing the Automation Pathway: Measures, Methods, and Results

In this section, I empirically evaluate my hypotheses using experimental and observational data. My conceptual framework examines how automation shocks trigger cultural grievances –perceived marginalization and nostalgic attitudes– which in turn drive 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. Additionally, by measuring how subjects' exposure to risks affects perceptions of nostalgia and marginalization, my experiment sheds 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 exposure to robots increased job insecurity, while Granulo, Fuchs, and Puntoni (2019) show that people preferred being replaced by robots over humans, reflecting a decline in pro-social sentiments when assessing their own job prospects.

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).[4,5] I implement a design-based experimental mediation analysis with double randomization of the treatment (exposure to automation risk) and encouragement of mediators (perceived marginalization and nostalgia).[6] 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 sample into treatment and control groups. Then, each group is randomly assigned to a mediation encouragement.

To provide an ecologically valid news consumption experience, in a realistic setting, I adopted and modified the tasks for respondents based on a study conducted by Lelkes and Westwood (2017). Respondents were presented with two news articles[7] and given the responsibility of evaluating them to assist a startup online news content platform in deciding which article to publish. In the treatment condition, participants were exposed to two news articles discussing job displacement caused by automation, focusing on either manufacturing jobs (robots treatment) or white-collar jobs affected by AI (AI treatment). 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 community affected by technological change (every subject read both). 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

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

[5] 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.

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

[7] 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).

> 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' nostalgic attitudes or perceived marginalization by asking them to complete a short writing exercise (autobiographical emotional memory task). The framing of this 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.[8] I designed this task to encourage emotions from respondents, based on previous work in social psychology and political science.[9]

After completing these tasks (reading and writing), participants were asked which article they would endorse for publication 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. They were then asked to describe their feelings about the articles (anger, fear, uneasiness, enthusiasm, or none) to check for the treatment effect.

[8] A respondent will be classified as cultural-grievances encouraged if assigned to write about either nostalgia or perceived marginalization.

[9] See examples in social psychology Xia, Wang, and Santana (2021), van Tilburg, Sedikides, and Wildschut (2015), and Newman et al. (2020), as well as in political science, for example, Rhodes-Purdy, Navarre, and Utych (2021*b*) and Busby, Gubler, and Hawkins (2019).

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. The political behavior questions encompassed various topics, such as support for a potential Trump candidacy in the 2024 presidential election, and evaluations of whether trade benefits American workers (core elements of neo-mercantilist foreign economic policies) or which policy should exist regarding legal immigrants.

Shifting attention to the observed mediators, I employed various questions previously utilized in psychology studies to measure nostalgic attitudes. 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 attitudes. To assess cultural discontent or what I refer to as perceived 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 (Rhodes-Purdy, Navarre, and Utych, 2021*b*).[10] Using these items on nostalgia and perceived marginalization, I constructed an index of cultural grievances. These indexes serve two purposes: (1) to examine the effect of the treatment (automation risk exposure) on cultural grievances, and (2) to assess compliance with the encouragement of the mediators.

To serve as manipulation checks for the main treatment 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

[10] 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."

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.[11] Mediation analysis has risen as a pivotal method to address this gap, unpacking the 'how' and 'why' behind social effects;[12] this method constitutes my primary empirical strategy. Using Baron and Kenny's (1986) 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

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

[12]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).

not guarantee that M or Y are not systematically linked to these error terms, potentially introducing bias.[13]

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 conditions. 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 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 1, 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 replaced 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.

[13]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).

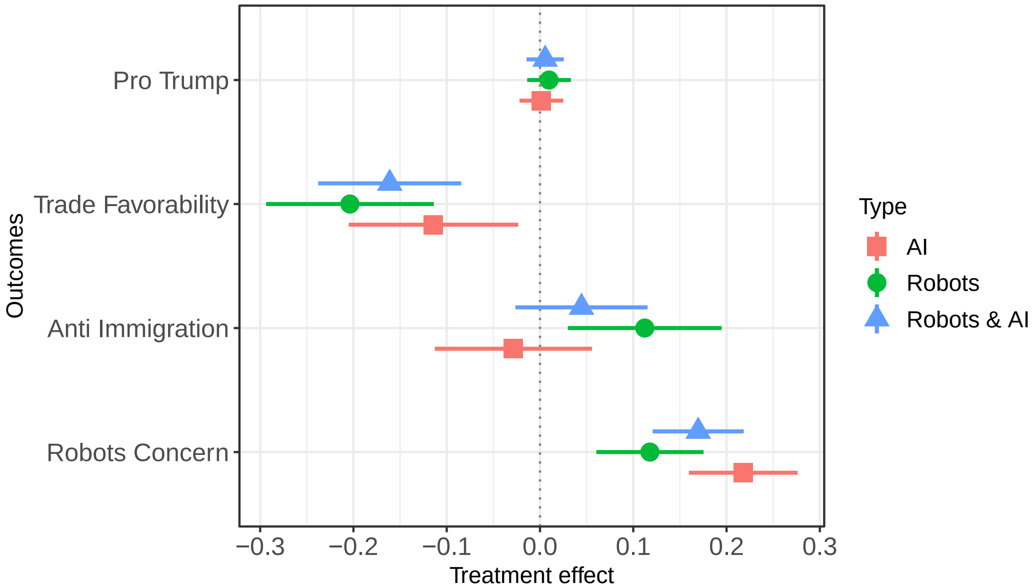

Figure 1: Total Effect of Exposure to Automation Risk (proxied as robots and AI).
Note: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related 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.

Figure 1 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.[14] 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.[15] 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).

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.[16] Nonetheless, the findings suggest that workers exposed to news of economic displacement may be predisposed to back right-wing populist candidates, who are more inclined to promote illiberal policies. For instance,

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

[15]The ATE regarding Donald Trump support is positive and statistical significant when instead of using a simple ATE we use matching on co-variates Figure B.1.

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

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 see as related to high-skilled immigrants, hence provoking less anti-immigration policy preferences 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 cultural discontent indicator, resulting in a change of about 23 percentage points (pp, see Figure 2). 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.

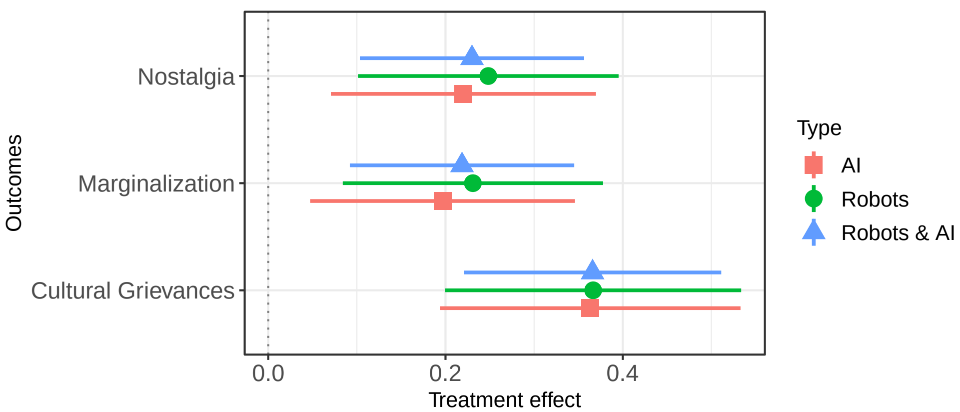

Figure 2: Treatment Effects of Exposure to Automation Risk on mediators.
Note: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related displacement (N=2,177), and 'Robots & AI' pools the data (N=3,133). Results for each mediator are shown, with dummy variables representing scores above the median. 'Nostalgia' reflects sentimentality for the past, 'Marginalization' denotes a perceived exclusion - cultural discontent, 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 mediator.[17] I estimate the impact of the mediator encouragement (writing task about nostalgia or perceived 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 3 presents the estimated effect using intent-to-treat (ITT) analysis, with random assignment serving as an instrument for compliance.[18] Compliers are defined as those with high mediator levels who also completed the writing task.[19] Task completion assessment relied on hand coders labeling each response as 'complier' or 'non-complier' based on the encouragement prompt's fulfillment.[20]

Figure 3 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

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

[18] 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.

[19] 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).

[20] 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).

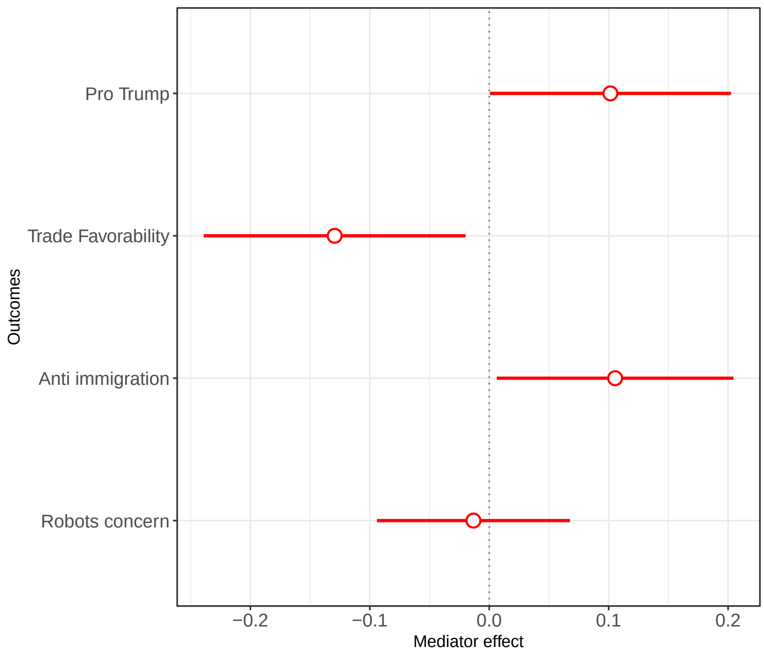

Figure 3: Mediator Effects on Outcomes, ITT
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as an instrument for compliance. The results for each outcome—'Pro Trump' (willingness 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.

trade and immigration favorably drops by 13 and 11 pp, respectively, for those randomly 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 2) and the mediator's effect on the outcome (Figure 3). 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.[21] These findings support **Hypothesis** 3, which posits the existence of a mediated path through which automation influences political attitudes.

These results show that negative economic shocks, such as those resulting from job automation trigger cultural grievances. These grievances, in turn, are linked with illiberal

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

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. Notably, these results align with recent debates suggesting that the appeal of populist leaders may stem more from their substantive policy positions than their rhetoric (Dai and Kustov, 2023). 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.

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.

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.[22] In this analysis, the dependent variable is the vote choice for right-wing populist parties. 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.[23] 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

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

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

recent technological change is likely to mean for the future of employment. This measure ranges from 0 to 1, with 0 representing no probability of computerization (e.g., recreational therapists), and 1 representing a fully computerizable task (e.g., telemarketers). As an alternative, I use Anelli, Colantone, and Stanig 2021's 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 perceived 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.[24]

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

[24] I acknowledge these questions imperfectly capture nostalgia, skewing towards collective pessimism, but they have been used in prior research (e.g., Steenvoorden and Harteveld, 2018).

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 cultural discontent. Columns 5 and 6 illustrate that a higher probability of job computerization is linked with diminished optimism about the future, thus increasing nostalgia.[25]

	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.

Subsequently, I turn to mediation analysis. Figure 4 and Figure 5 present results consistent with both my theory and experimental findings regarding the average causal

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

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**.

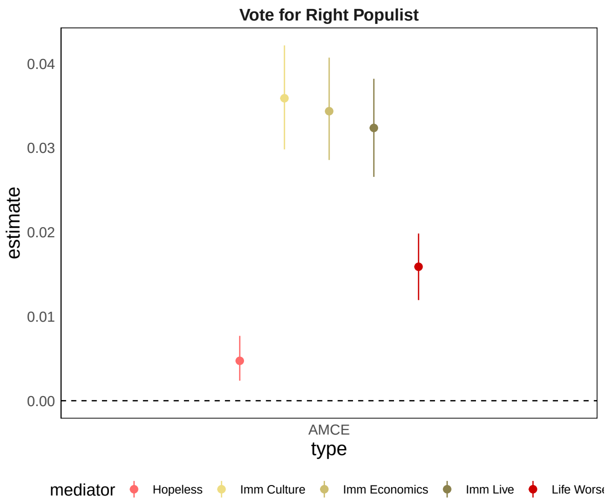

Figure 4: Mediated effect of automation through cultural beliefs on political behavior.

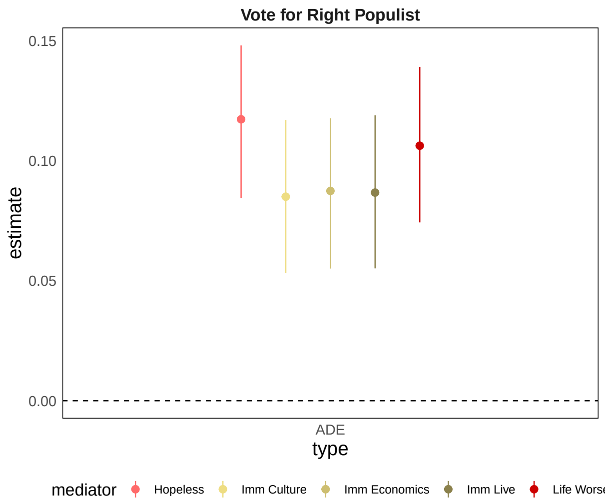

Figure 5: Direct effect of automation on political behavior.

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 attitudes, 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.

Conclusion

This article shows, with consistent evidence from a survey experiment and observational analyses, that exposure to automation risk increases support for policies often advanced by right-wing populists, including protectionism. Part of this shift operates through cultural grievances, especially cultural discontent and nostalgia. The implication for democratic politics is clear: when workers anticipate displacement, they become more receptive to exclusionary and restorative appeals, potentially eroding liberal-democratic norms.

These findings help clarify how structural economic change reshapes the political landscape. On the demand side, automation risk shifts both policy preferences and cultural grievances, making economically threatened workers more likely to support right-wing populist parties and candidates. On the supply side, such shifts create clear opportunities for political actors: they can combine distributive policies with illiberal overtones—such as higher import tariffs—with appeals to nostalgia and cultural discontent. The political resonance is strongest when cultural threats and economic grievances reinforce one another, as in Trump's tariff proposals against China, which fused protectionist economics with nationalist symbolism.

Taken together, these patterns speak to broader debates on the sources of populist support. Rhodes-Purdy, Navarre, and Utych (2023) argue that economic shocks can ignite negative emotional responses leading to democratic discontent; Roberts (2024) argues that populism grows where mainstream parties leave representation gaps; and Berman (2021) links the rise of right-wing populism to social-democratic failures to offer credible responses to globalization. The backlash exposes limits of party systems, especially their difficulty representing deep social cleavages. By highlighting automation-induced nostalgia and cultural discontent, this study identifies one such cleavage. Unless democracies restore social protection and voice, illiberal populism will continue to gain ground.

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: perceived 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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ONLINE APPENDIX

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 attitudes 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 1

	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 1

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 1

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 1

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 1

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

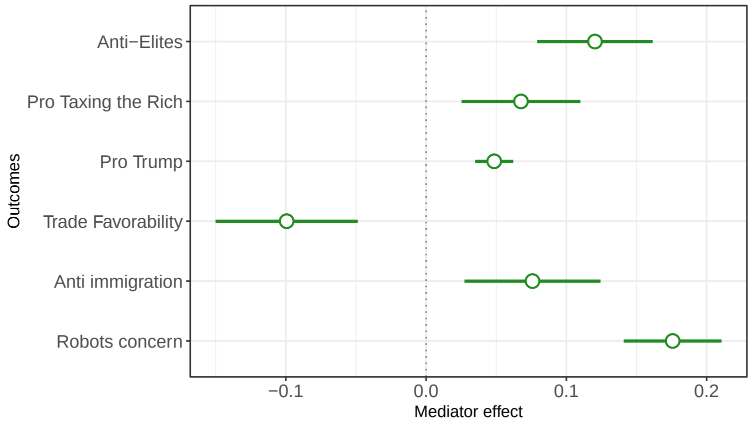

Figure B.1: Total Effect of Exposure to Automation Risk (proxied as robots and AI), using Matching. *Note*: This figure shows the ATE of exposure to job-threatening news against a control group of 1,182 subjects. The treatments robots & AI have been pooled (N=3,133). Each row in the figure shows a set 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.[26]

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

[26] 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.

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 2

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 2
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 perceived 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 2
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 perceived 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 2

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 perceived exclusion, and 'Cultural Grievances' merges both indices.

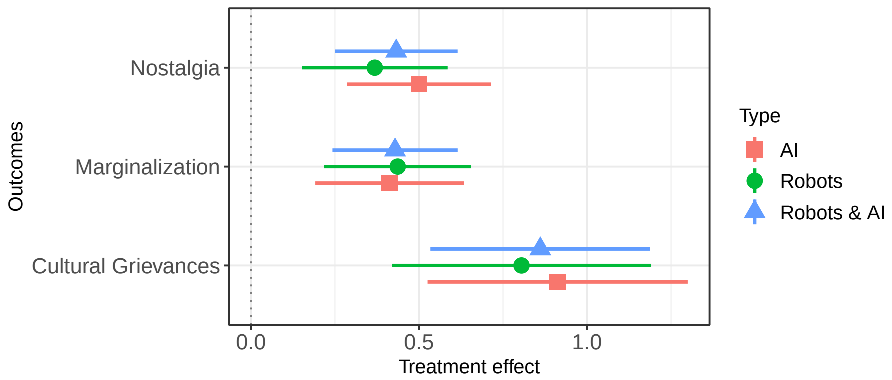

Figure D.2: Treatment Effects of Exposure to Automation Risk on mediators. *Note*: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. 'AI' represents the treatment effect of AI-related job displacement (N=2,138), 'Robots' for machine-related 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.

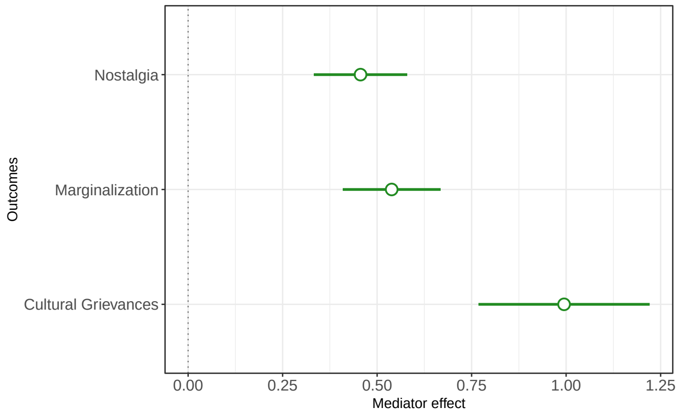

Figure D.3: Treatment Effects of Exposure to Automation Risk on mediators, using Matching. *Note*: This figure shows the effect of exposure to job-threatening news on the mediators against a control group of 1,182 subjects. Treatments were pooled 'Robots & AI' (N=3,133). Results for each mediator are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

D.2 Effects of M on Y, refers to Figure 3

	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 3

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 3: OLS & Matching

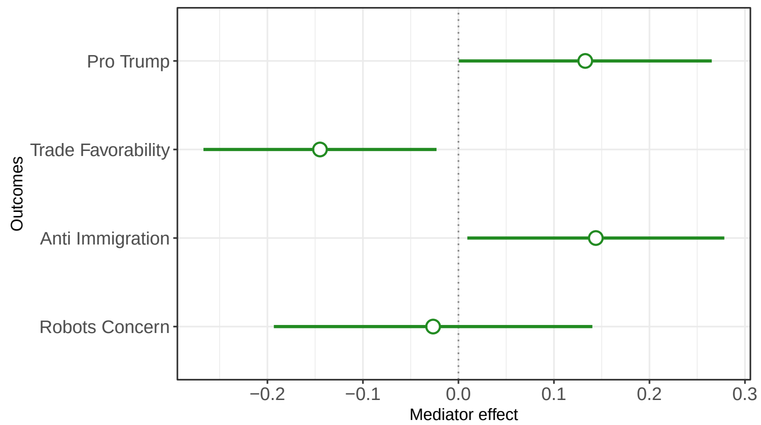

Figure D.4: Encouragement Effects on Outcomes, OLS
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as a treatment variable and OLS, with control variables (education, race, income, 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).

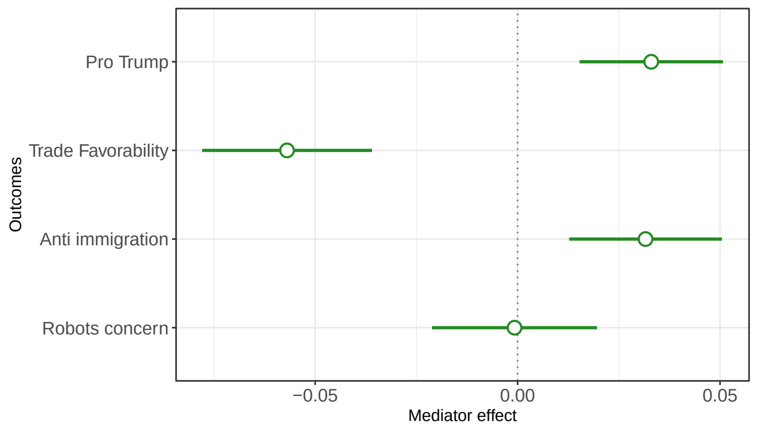

Figure D.5: Encouragement Effects on Outcomes, Using Matching
Note: This figure shows the impact of mediators on key outcomes in a sample of 3,133 respondents, with 1,816 receiving encouragement and 1,317 not, using random assignment as a treatment variable and matching on covariates (education, race, 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 3: 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.

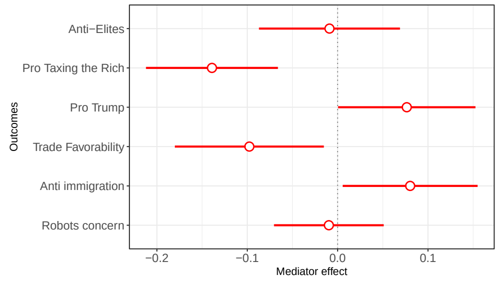

Figure D.6: T=0.842 (p-value<0.4)

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.

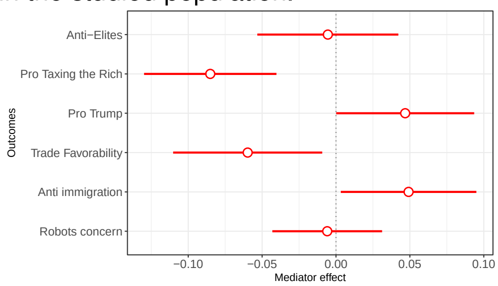

Figure D.7: T=0.18 (p-value<0.5)

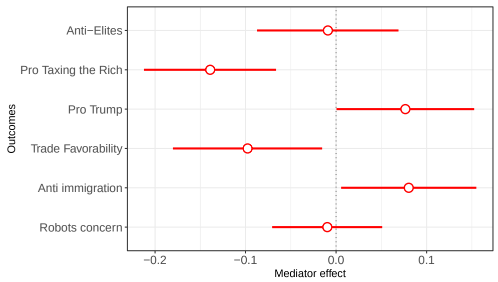

Figure D.8: T=0.842 (p-value <0.40)

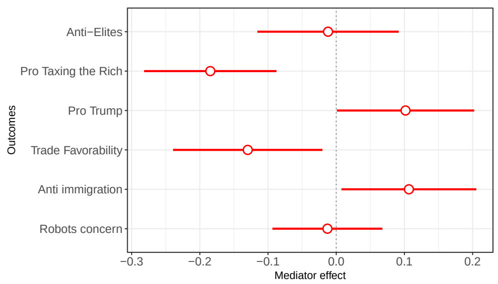

Figure D.9: T=1.036 (p-value<0.3)

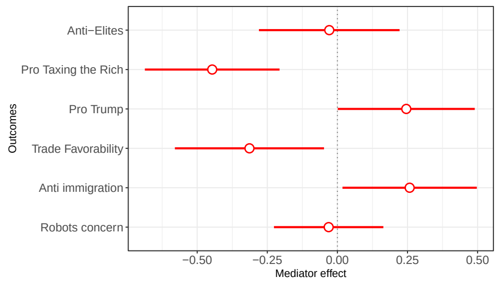

Figure D.10: T=1.646 (p-value<0.1)

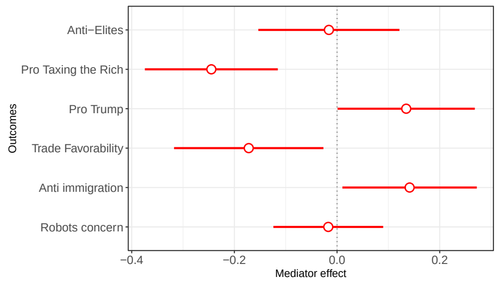

Figure D.11: T=1.282 (p-value <0.20)

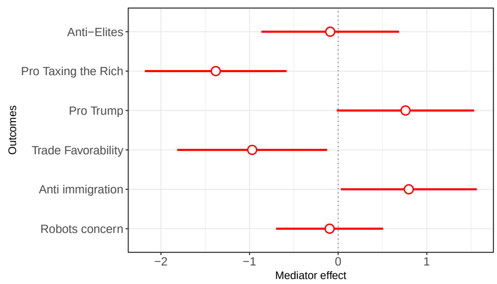

Figure D.12: T=1.962 (p-value<0.05)

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)

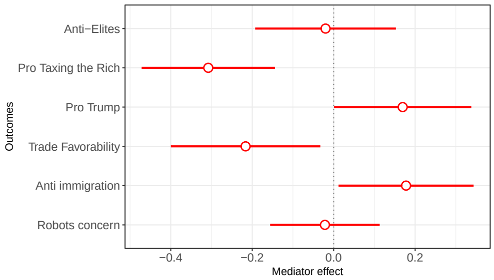

Figure D.13: Compliance defined as: 1) high levels of the mediator relative to non-encouraged (t=1.036), 2) task completion defined as hand coders and more than median words.

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.

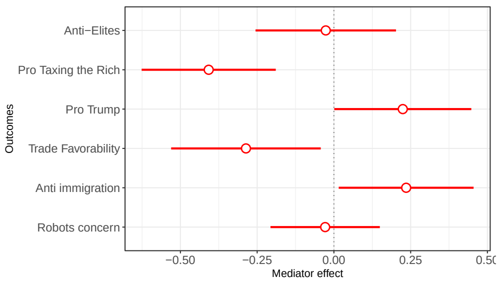

Figure D.14: High levels of the mediator as higher than the median in the sample, and hand-coders as compliers.

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.

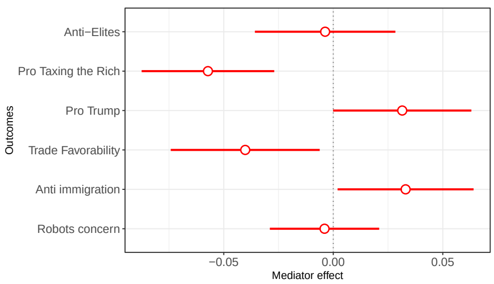

Figure D.15: Compliers only based on hand-coders annotation of the writing task.

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:

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

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

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

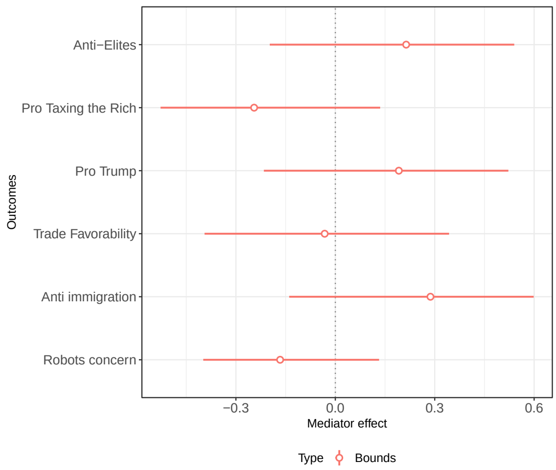

Figure D.16: Mediator Effects on Outcomes, Bounds

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 $\text{SE}(p_1 p_2)$

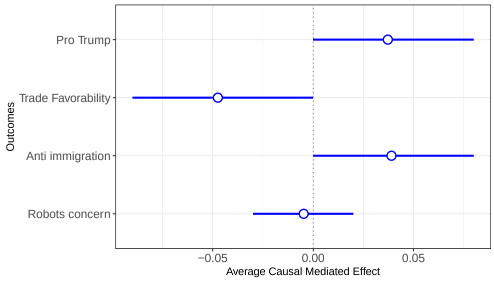

Figure D.17: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to those non-encouraged (t=1.036), and 2) task completion as hand-coders.

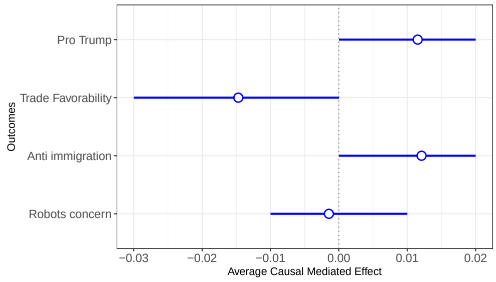

Figure D.19: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to median level in the sample, and 2) task completion as more than median words.

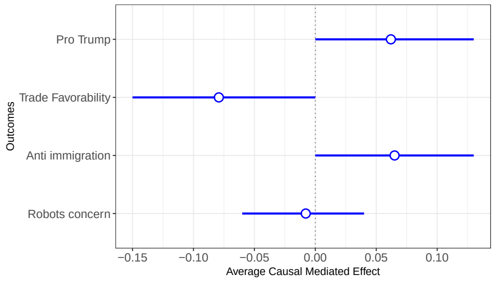

Figure D.18: Causal Mediation Effects
Note: Compliers defined as 1) high level of the mediator relative to those non-encouraged (t=1.036), and 2) task completion as hand-coders & more than median words.

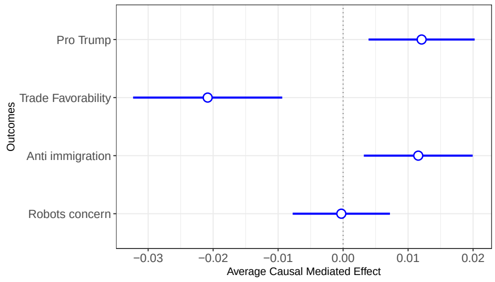

Figure D.20: Mediated effect, with the encouragement effects on outcomes estimated using Matching

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 perceived marginalization rather than a direct influence on populism. Specifically, exposure to automation risk accounts for approximately 26% of this effect by altering nostalgic attitudes 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.

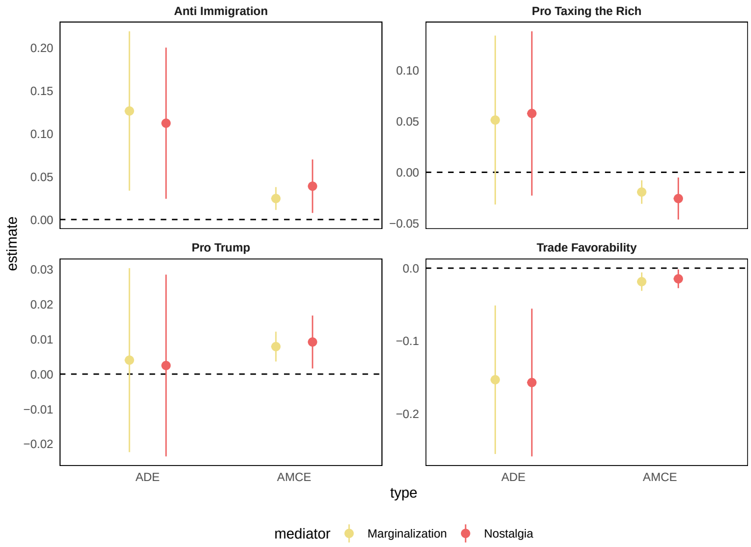

Figure D.21: Estimates of Causal Mechanisms using Survey Data

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 perception 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).

D.7.1 Sensitivity Analysis.

	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 4 & Figure 5. **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 4 & Figure 5.

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 4 & Figure 5.

E.3.2 Sensitivity Analysis associated to Figure 4 . 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 4.

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.