

Why Different Economic Shocks Have Different Political Effects*

Leonardo Baccini

McGill University & CIREQ

Costin Ciobanu

RHUL & McGill University

Krzysztof Pelc

McGill University

Abstract

While the evidence suggests that technological change is to blame for more labor dislocation, offshoring remains a far more frequent target of attacks by populist leaders. What explains this discrepancy? We argue that the most relevant aspect of economic shocks is the perception of what groups gain and lose, and how this relates to individuals' own identity. Offshoring proves politically potent because it benefits an identifiable out-group, while automation does not. Using a mix of observational and experimental evidence, we show that offshoring makes individuals more likely to turn to political leaders who appear less constrained by rules, and more willing to employ force and adopt divisive policies. Yet this baseline result conceals crucial variation along identity lines. These come down to beliefs about how a given shock affects one's in-group. Specifically, individuals who believe that more white workers are affected by offshoring appear most likely to respond to offshoring by adopting populist values. Our findings help explain why some economic shocks provide a greater opportunity for political candidates willing to capitalize on divisions between identity groups.

Keywords: Automation, offshoring, identity politics, populism, US.

Word count: 9,422.

*. We thank Francesco Amodio, Elissa Berwick, Aengus Bridgman, Aaron Erlich, Diana Mutz, Thomas Sattler, and Stephen Weymouth for suggestions on the survey experiment. We also thank participants to Princeton's Niehaus Center "The Backlash: What's Next" Workshop (2022) and to the 2022 APSA Annual Meeting for their feedback. Sean Nossek provided outstanding research assistance. The usual disclaimers apply. The analysis with the ANES data was performed in the Virtual Data Enclave from the Inter-university Consortium for Political and Social Research (ICPSR). Funding for this research was provided by the SSHRC Insight Development Grant, Canada (grant agreement 430-2018-1145) and the FQRSC Team Grant (grant agreement 243479 2017-SE-196451). REB approval for the survey experiment was obtained from McGill University (REB #21-01-034, 21th January 2021). REB approval for Restricted Data Access at ANES was obtained from McGill University (REB #21-08-035, 25th August 2021). The pre-analysis plan registered with EGAP is available here: <https://osf.io/wkhy2>.

1 Introduction

The Kroger Company, founded in 1883, is America’s largest grocery retailer. In April 2021, Kroger built its first e-commerce plant in Monroe, Ohio. Staffed by over a thousand robots using machine learning to optimally package groceries for delivery, the plant has successfully automated tasks that until recently were handled by large numbers of human workers.¹ Such moves have been criticized by some. As the president of the United Food and Commercial Workers Union which represents grocery workers put it, “Six months ago, all these workers were essential. Everyone was calling them heroes. Now, they’re trying to figure out how to get rid of them.”

But the discontent did not escalate further. Grocery workers did not mobilize, Ohio policymakers did not bemoan the jobs that could have been, and the White House has not introduced policies to protect workers from the labor displacement effects of similar technologies. If anything, US tax regulation actively incentivizes the capital investments required for automation. This lack of political pushback is especially puzzling given how automation has become a leading source of labor displacement across OECD countries.

By contrast, policymakers have been quick to condemn another cost-saving technology: the offshoring of jobs to other countries. In a well-known example, outsourcing plans by the Carrier furnace plant in Indianapolis became one of the focal points of Donald Trump’s 2016 presidential campaign. Democrats are also critical of offshoring: in 2020, President Biden proposed a 10% surtax on American companies that produce goods and services overseas and sell them back on the U.S. market.² Such political condemnation exists in spite of how offshoring accounts for fewer job losses than automation, and both are thought to increase productivity on average.

What explains this discrepancy? Stated more generally, which economic shocks generate demand for radical change and the political candidates who promise to deliver it? By contrast, which shocks are dismissed as part of the natural course of economic activity? As uneven growth and losses in manufacturing employment have coincided with a wave of right-wing populism across industrialized democracies, few questions have garnered as much scholarly attention. Studies from economics, po-

1. <https://ir.kroger.com/CorporateProfile/press-releases/press-release/2021/Kroger-Delivery-Introduces-Americas-First-Customer-Fulfillment-Center/default.aspx>.

2. “Biden proposes a tax penalty for offshoring and new credits for manufacturing investments.” CNBC. 2020. <https://www.cnbc.com/2020/09/09/biden-proposes-tax-penalty-for-offshoring-tax-credit-for-us-investment.html>.

litical science, and sociology (Walter 2010; Jensen et al. 2017; Mutz 2018; Norris and Inglehart 2019; Gidron and Hall 2017; Colantone and Stanig 2018; Autor et al. 2020; Di Tella and Rodrik 2020; Broz et al. 2021) have taken to explaining the various ways that economic shocks and political upsets might be linked. The result has been growing recognition of how cultural and economic forces have both played an important role in the populist backlash (Bisbee et al. 2020) of recent years. Yet we still lack a good understanding of the underlying mechanisms tying these forces together.

On its face, the populist backlash against globalization is puzzling for a number of reasons. Indeed, most workers in OECD countries are employed in the services sector, which is largely shielded from trade competition (Di Tella and Rodrik 2020). The US economy has been the focus of the preponderance of this research, but given the size of its internal market, it is in fact least exposed to trade, relative to other OECD countries. The number of layoffs due to technology is also significantly greater than those due to globalization; yet it is trade and offshoring that have borne the brunt of the political condemnation (Wu 2021).

Meanwhile, automation may in fact have a greater political impact than anecdotal evidence would suggest, with a number of findings linking automation to the election of populist candidates on both sides of the Atlantic (Im et al. 2019; Anelli et al. 2021; Milner 2021), in a claim encapsulated by Edsall’s (2018) view that “robots can’t vote, but they helped elect Donald Trump.” Yet because the underlying findings are based on observational evidence, it remains difficult to tease out the effect of automation from that of globalization.

In response to this continued ambiguity, we seek to shine a light on the causal relation between different economic shocks and political demands. The premise of our paper is that the political effects of offshoring, compared to those of automation, conceal crucial heterogeneity. Different groups respond differently to each one, in ways that tell us a great deal about the broad question of how economic shocks translate into political upsets. Our analysis thus exploits variation on two key parameters: the type of shock and the individual’s identity group. Using these, we measure the extent to which individuals perceive the effects of automation vs. offshoring through the lens of identity.

In doing so, we argue that the most relevant aspect of economic shocks is the perception of who gains, and who loses. It is at this early stage, in a clash over basic economic facts, that identity begins to manifest itself. In this way, offshoring activates identity concerns in ways that automation does not, because it benefits an identifiable out-group, foreign workers. As a result, offshoring politically

activates those who view themselves as part of the historically dominant group, which they perceive is losing at the expense of some “other”.

Our argument thus fits into an emerging literature that emphasizes the role of identity as the lens through which individuals perceive economic shocks. As public opinion models have swung between an egotropic approach that considers pocketbook effects to a sociotropic approach that highlights the importance of the national economy for individual evaluations (Mansfield and Mutz 2009; Colantone and Stanig 2018), this recent wave of findings has instead emphasized identity groups as the relevant frame of comparison (Guisinger 2017; Jardina 2019; Mutz 2018; Baccini and Weymouth 2021; Bonomi et al. 2021; Ballard-Rosa, Jensen, et al. 2022; Ballard-Rosa, Goldstein, et al. 2022). Our approach is especially closely aligned with that of Jardina (2019), who shows how a subset of white Americans with a heightened sense of group identity accounts for the cleavages that populists like Donald Trump capitalize on.

Our empirical strategy proceeds in two parts. First, relying on the American National Election Studies (ANES) Restricted Data Access, we provide evidence that white Americans whose jobs are vulnerable to offshoring are more likely to hold populist attitudes following layoffs than if their jobs are vulnerable to automation. We find that the same is not true for non-whites. Second, using an original experimental vignette study covering 3,505 US citizens, we offer a more direct test of our argument and the underlying mechanism, by homing in on those individuals who respond to offshoring-induced layoffs with more populist attitudes. In particular, we examine how beliefs about the distributional effects of economic events, as well as inferences drawn from beliefs, differ along identity lines.

The experimental analysis delivers two main findings. First, we show that technology-induced layoffs have a smaller effect on overall demands for a populist political response than layoffs due to offshoring. Despite a growing amount of work at the nexus of globalization and technological change, this is to our knowledge the first attempt to causally identify the effect of automation vs. offshoring events on populist attitudes.

Second, we assess respondents’ beliefs about the underlying economic facts. When asked to guess the demographic make-up of a given number of layoffs due to offshoring, race sharply skews perceptions—more so than gender, education, or industry cleavages. Whites believe that their identity group accounts for more layoffs due to offshoring, consistent with the notion that white Americans are more likely to view themselves as “prototypical of the nation” (208). These findings are akin to

what other scholars have termed “racialized economics” (Sides et al. 2018), whereby economic facts are refracted through identity.

These beliefs about the distributional effects of different economic shocks allow us unique purchase on variation in attitudes within identity groups. Indeed, we know from prior research that group identity does not affect all members of a given group evenly (Jardina 2019). Accordingly, we show that the underlying beliefs about distributional consequences of shocks emerge as a strong predictor of the extent to which offshoring—but not automation—leads to demands for a radical political response. Those who believe that more whites are affected by offshoring are also more likely to respond to offshoring by calling for a radical political leader. Once again, the same does not hold for automation.

In sum, we argue that beliefs about economic shocks are refracted through a racial identity lens. And it is these refracted beliefs—specifically about the distributional effects of economic shocks—that drive the demand for a radical political response to economic shocks.

Our findings hold implications for a number of key questions in political science. Among these is the enduring puzzle of why the populist playbook has been so successful in industrialized democracies. Even if economic pain is evenly distributed across different identity groups (Gould 2021; Benguria 2020; Wallach and Rangel 2021), different perceptions of the same economic events means that some shocks represent a greater opportunity for political candidates willing to capitalize on divisions between identity groups.

2 Background: How Do Economic Shocks Differ?

In a recent article, Gordon Hanson (2021), one of the authors of the original 2013 China Shock study—which was largely responsible for first drawing scholarly attention to the geographically-concentrated employment losses in US manufacturing due to trade competition—argues that “because the scarring effects of job losses are the same whether imports, robots, or a virus is responsible, responses to the damage should not depend on the identity of the culprit.” In this article, we examine some of the political reasons to think otherwise. Our main claim is that different types of economic shocks may in fact generate different political responses.

First, there may be reasons to distinguish between trade and technology shocks on strictly economic grounds. Both offshoring and automation offer consumers analogous benefits through reduced

prices, but some argue that offshoring improves a firm’s cost structure without necessarily delivering productivity improvements, as automation can. However, recent findings have challenged the conventional understanding of automation’s effects on productivity. Communities that have witnessed higher adoption of industrial robots have also experienced more unemployment and wage declines. In many cases, automation may lead to labor displacement without much in the way of productivity increases (Acemoglu and Restrepo 2018, 2020). These findings have led to congressional testimony about “excessive automation” by prominent economists, and considerable media attention.³

In the face of such ambivalence over the effects of different economic shocks on productivity and local labor demand, we argue that what Hanson (2021) calls the “identity of the culprit” is in fact crucially important for political reasons. Indeed, when economic facts are refracted through the lens of group identity, who the “culprit” is also determines individual beliefs over who bears the greatest harm. These beliefs, in turn, lead to political demands that populist political entrepreneurs are especially well-placed to exploit. The result is that some shocks are more likely to lead to calls for radical political action than others. To show why this is, we compare reactions to two types of economic shocks—jobs displaced by technology versus jobs sent offshore—against reactions to run-of-the-mill bankruptcies due to business cycle fluctuations.

While automation is widely thought to be a greater source of labor dislocation than trade and offshoring, it has been the target of far less political opprobrium.⁴ Yet the relationship between automation and political outcomes has thus far remained unclear. Frey et al. (2018) argue that automation contributed to Trump’s victory in the 2016 presidential elections. Similarly, in the European context, both automation and trade shocks have been associated with increased support for nationalist and radical-right parties (Colantone and Stanig 2018; Im et al. 2019; Anelli et al. 2021; Milner 2021). Specifically, findings have shown that the adoption of robots has coincided with a rise in anti-immigrant sentiment, which in turn brought populist leaders to power in countries across Europe. These findings are based on observational evidence, making it difficult to tease apart the effect of automation from that of globalization, especially since these interact in various ways: the geographic

3. See Daron Acemoglu’s Congressional testimony to the House Committee on the Budget. September 2020, <https://www.congress.gov/116/meeting/house/111002/witnesses/HHRG-116-BU00-Wstate-AcemogluD-20200910.pdf>. For representative media coverage, see New York Times: “Economists Pin More Blame on Tech for Rising Inequality.” <https://www.nytimes.com/2022/01/11/technology/income-inequality-technology.html>.

4. For an extensive literature review of the effect of automation and digitalization on voting behavior, see Gallego and Kurer (2022).

distribution of labor-saving technology matches the geographically-concentrated aspect of trade exposure (Autor et al. 2013; Autor et al. 2020): industrial robots have their greatest displacement effects in manufacturing-dependent commuting zones that are also vulnerable to import competition and task offshoring (Acemoglu and Restrepo 2018). And technological advances may themselves facilitate offshoring by reducing the skills required to carry out specific tasks (Goos et al. 2014). On the other hand, automation reduces the wage differential between countries and economizes on transportation costs, affecting incentives to offshore jobs in the first place (Bonfiglioli et al. 2021). Many firms thus view the two as substitute means of cutting costs (Owen 2020).

Meanwhile, several studies have tried to account for why automation would be a less appealing political target than offshoring. For one, automation in general, and digitalization in particular, generates a large set of winners among voters, who are in turn likely to have political preferences in line with the status quo (Gallego et al. 2022). Some look to the nature of the shock itself: offshoring may be more visible (Wu 2021), since it often concerns entire factories closing down and moving abroad, while robots can gradually replace tasks previously performed by humans without raising much attention. Automation, moreover, brings to mind progress and innovation. In capital-rich countries, it may thus be thought to bolster an existing comparative advantage in capital-intensive goods, whereas offshoring underscores their comparative disadvantage in labor (Chaudoin and Mangini 2021). Or it may be that technological change is seen as an unstoppable force, operating entirely outside of any political process (Lee 2021). By contrast to these explanations, we focus on how different “culprits” lead to different perceptions of harm, and how these perceptions vary across identity groups.

2.1 The Role of Identity

Drawing on recent findings in American politics, we focus on white Americans as the historically dominant, majority identity group in the US. In recent decades, whites have experienced a rising threat to their position (Jardina 2019) as a result of demographic, economic, and cultural factors, in ways that have manifested politically. As Mutz (2018) puts it, for the first time since European settlers arrived in the country, white Americans are being told they will soon become, strictly speaking, a minority group. The election of Barack Obama in 2008 was a watershed moment in American racial attitudes: as Sides et al. (2018) show, party coalitions grew increasingly “racialized” even while Obama was still in office, in ways that came to the fore during the 2016 presidential election. Recently arrived

immigrants become a natural target for populist politicians, since they embody the “other” in two ways: first as foreigners, and then as minorities in the country taking “our” jobs and draining public resources.⁵ When asking how various groups might differ in their evaluations of the same economic reality, the cleavage between white and non-white Americans has thus become the most salient line of demarcation (see for example Mutz et al. (2021)).

Our emphasis on identity groups explains a puzzling aspect of the recent populist backlash: an individual’s own material condition may be unchanged, yet they may nonetheless worry that the fortunes of their group are declining, and demand that politicians take action in response. These evaluations have a strong zero-sum aspect: if another identity group is rising, then one’s own group must be declining (Jardina 2019, 141). This view is aptly summarized by Sides et al.’s account of the 2016 US election: “The important sentiment underlying Trump’s support was not ‘I might lose my job’ but, in essence, ‘People in my group are losing jobs to that other group’” (Sides et al. 2018, 8). Our theoretical expectations build on this zero-sum aspect.

In this way, the key distinction between offshoring and automation is that the first benefits an identifiable out-group—foreign workers—while the second does not. Foreign workers pose a greater threat to those who perceive themselves as belonging to a historically dominant, high-status group; robots pose no equivalent threat. This makes the difference in the response to these two economic shocks analytically useful for our purpose. Our research design thus relies on eliciting beliefs about who gains and loses from different economic shocks, and seeing how these relate to political demands.

One way in which identity may matter is by generating more distress in the face of the same economic event. But identity can also intervene one step prior, in the very reading of the shock. As Sides et al. (2018) demonstrated, whites with a stronger racial identity had a more negative view of the economy during the Obama administration than non-whites. That is, they systematically underestimated the actual growth rate in the country, in an illustration of what Sides et al. (2018) call “racialized economics,” whereby economic reality gets refracted through an identity lens. We expect that a similarly biased reading of economic reality may be present in the perception of economic shocks. Specifically, we test whether white Americans, because of their greater concern about the ‘other’, both foreign and domestic, believe that the average offshoring layoff affects more white Americans. If this

5. See a representative statement from Donald Trump, who asserted that immigrants are “taking our jobs. They’re taking our manufacturing jobs. They’re taking our money. They’re killing us.” In: Sides et al. (2018, 176).

biased reading of economic events is driven by identity concerns, then the same cleavage should not be as apparent in the case of automation. In other words, beliefs about group identity should explain not only reactions to economic events, but beliefs about the economic events themselves.

Following both Sides et al. (2018) and Jardina (2019), there is reason to think that it is precisely those white Americans who have more biased views of offshoring events that are most likely to view offshoring as a political matter. The same people should then be more likely to demand radical political action in response.

2.2 A Populist Opportunity

One striking aspect of the recent rise of populist, and especially right-wing populist candidates across developed democracies, has been the remarkable consistency of their political messaging. As the leading theorist of populism Jan Werner Müller (2016) puts it, the core claim of populism is that “only some of the people are really the people.” Populist leaders promise to represent the “real people” in opposition to the “other.” This “other” is made up of foreigners abroad, and ethnic, religious, or sexual minorities domestically. By comparison, robots do not represent an equally potent scapegoat, because they do not fuel the same zero-sum concerns.

In terms of policies, populist candidates have manifested greater willingness to break existing commitments, especially at the international level, in attempts to reaffirm national state sovereignty. They have been suspicious of trade agreements and supranational institutions like the European Union. They often, though not always, tend towards isolationism and trade protectionism. Yet it is the pushback against immigration that may be the most reliable hallmark of populist candidates. This follows intuition, insofar as immigrants can represent both the foreign and the domestic “other.” Populist political entrepreneurs have also shown more willingness to suspend long-established norms, including core democratic rules, and greater readiness to rely on force as a means of reaching desired policy outcomes.

For these reasons, populist candidates are especially well-placed to respond to grievances arising from the perceived decline of historically dominant identity groups. In the case of the US, that group is made up of white Americans with strong racial identity. To these individuals, offshoring should look different from automation, even when they are said to result in the same number of layoffs. Since it benefits outsiders, offshoring should be seen as a greater threat to insiders. Note that this expectation

is far from obvious: it relies on individuals to (i) make a link between a local labor shock and its effects on foreign workers, then (ii) draw inferences about how benefits to the out-group negatively affect the in-group that they see themselves a part of, domestically and globally, and (iii) conclude that more populist leaders are better placed to address the problem, by virtue of their willingness to push back against out-group members. Building on the American politics literature cited above, we propose that this is precisely the thought process these individuals should go through. We test this expectation in our analysis below.

While we are interested in what accounts for the “populist opportunity” provided by economic shocks, ours is principally a demand-side account. We view populist platforms as a response to a set of recurrent demands for radical political action by disenchanting audiences across developed democracies. This is not to take away from the ability of populist candidates to manipulate and magnify the latent perceptions—our premise is simply that such perceptions must already be present for there to be something worth manipulating. We thus see the demand side as causally prior on the whole, which is why we focus on it here. Next, we present the theoretical expectations that allow us to test the different parts of the argument.

3 Theoretical Expectations

3.1 *Baseline Expectation: Automation vs. Offshoring*

Our first aim is to account for the observation that politicians appear less concerned by jobs lost to robots than those lost to international trade, by showing that policymakers’ behavior mirrors individual views, on average. To address this puzzle, we derive a set of expectations which we test in an experimental setting, which allows us to better pin down causal direction.

Existing work has shown that offshoring is different from other types of layoff events. Most recently, Di Tella and Rodrik (2020) show that offshoring leads to greater calls for trade protectionism, as compared with technology and demand shocks. This is perhaps not altogether surprising, since offshoring is a trade activity: production is transferred abroad and the product is reimported into the country. As such, it can be tackled more readily through trade protectionism than a technological shock would be.

By contrast, we are interested in a broader and more insidious political effect. We expect that

individuals view one type of economic shock as posing a greater threat than the other, and that this concern will be especially pronounced among members of the historically dominant group. We thus begin by asking whether individuals think that a given shock is an issue that political leaders should try to prevent in the first place. Then, we ask what type of leader individuals see as best suited for preventing layoffs of one kind or the other. As we argue above, the defining characteristic of offshoring is that it triggers latent fears about losing ground to some “other”. Populists offer more radical solutions aimed at such concerns, lashing out against both foreign workers and immigrants within the country. Rather than asking respondents about direct government actions—like trade protection or welfare compensation—we thus test whether the type of shock has effects on what kind of leader respondents think is best suited to handling the situation. In sum, we expect to see a greater embrace of populist leaders in response to offshoring than in response to a shock of the same magnitude caused by technology.

To test this expectation, we rely on the literature on populism to construct a composite portrait of a populist leader: in our telling, this would be (i) an outsider rather than an experienced politician, (ii) who listens to the people, rather than experts, (iii) who does not feel constrained by the rules to serve people’s needs, (iv) who might show greater willingness to use force to bring about desired change, rather than condemning violence under all circumstances, and (v) who does whatever it takes to help their local constituents, even if it upsets other people in the country. We test respondents’ demand for each of these traits separately, but we then follow the literature in examining populism’s constituent components (Hunger and Paxton 2021; Silva et al. 2022; Neuner and Wratil 2020; Jagers and Walgrave 2007). Specifically, we distinguish between “thin” populism (which includes people-centrism and anti-elitism) and “thick” populism⁶ (which refers to substantive policy positions and which we operationalize as anti-liberal-democratic values). This operationalization is also informed by recent work showing how illiberal, authoritarian values explain the link between economic shocks and the rise of populism (Ballard-Rosa, Jensen, et al. 2022; Ballard-Rosa et al. 2021). Our three

6. There remains ambiguity in the literature over the *thin* vs. *thick* populism distinction. Jagers and Walgrave (2007), who depict populism as a political communication style rather than an ideology, include in the thin category only people-centrism (appeals to the people), whereas anti-elite feelings (anti-establishment ideas) and the exclusion of certain out-groups are considered thick populism. Closer to our work, Neuner and Wratil (2020) distinguish between thin ideology (or populist valence, understood in terms of anti-elite and people-centric appeals) and thick ideologies (in their analysis, policy positions related to anti-immigration, anti-globalization, and pro-redistribution policies). Silva et al. (2022) generally maintain this distinction, but talk about “extreme positions on policy issues” such as immigration or taxation.

measures of thick populism (using force, undermining the rule of law, and abetting divisiveness) fit with conceptions of populism as “democratic illiberalism” (Pappas 2019).

3.2 Automation vs. Offshoring and Perceptions of In-Group Harm

Our first expectation says little about *why* the political response to layoffs due to technology versus trade is any different. It could be due to beliefs about US comparative advantage, or positive associations of technology-driven change with innovation, or a prevalent sense that technological progress is a structural change that cannot be stopped.

Our own explanation is that this baseline effect conceals crucial variation between and within identity groups: if individuals read economic shocks through the lens of identity, then we should expect that the combination of historically dominant group membership and economic shocks benefiting out-groups should prove most potent. In the case of the US, the resulting testable implication is that white Americans should be more likely to perceive layoffs due to offshoring as a threat, and that they should be more willing to act on that threat politically.

If concerns over offshoring come down to concerns about “the other”, then it follows that we should not see the same differences between identity groups when it comes to automation. Indeed, there is no clear reason why some groups would be inherently more enamored of (or more threatened by) innovation. If we observe this differential effect, this would support our contention that individuals read economic shocks through the lens of group identity.

3.3 Distributional Effects of Shocks: Perceptions of In-Group Harm

There is reason to believe that beliefs about the very nature of an economic event are also distorted by an identity-based reading. Recall that perceptions of the fortunes of identity groups are known to have a strong zero-sum aspect (Jardina 2019, 141). If so, it follows that historically dominant identity groups may not only exhibit greater concern about economic shocks that benefit an out-group, but that they may also interpret the same event as disproportionately affecting their in-group. Applied to our setting, we expect that white Americans should be significantly more likely to overestimate the number of white Americans affected by offshoring, compared to automation.

Also following Jardina (2019), we believe that not all white Americans exhibit similar levels of racial identity. As a result, there should be considerable variation in perceptions of in-group harm

flowing from economic shocks, like offshoring, that benefit out-groups. This variation is analytically meaningful. That is, beliefs about who is affected by offshoring might be an especially good indicator of whether individuals demand radical political action in response to offshoring, versus automation.

Who might be more likely to overestimate the number of white Americans affected by offshoring? Here, our expectations are largely derived from the literature on American identity politics: we expect that older, rural, male Republicans with no college degrees, who hold more nationalist views, should be most likely to hold strong racial beliefs that manifest in an overestimation of the proportion of white Americans harmed by an offshoring event. That, in turn, should magnify the political response in the face of offshoring—but not automation.

The other benefit of our continuous measure of beliefs about who is harmed by an economic shock benefiting the out-group is that it may be less vulnerable to social desirability bias.⁷ This variable thus allows us to get at the question of how identity affects the demand for populism in the face of different economic shocks. This is the question we examine next.

3.4 Group Identity and Radical Political Action

We combine the above reasoning to derive expectations over the heterogeneous effects on our main outcome of interest, the demand for radical political action. We can test these expectations against both our experimental results and observational data. As mentioned above, our baseline prediction is that automation leads to a lesser perception of harm than offshoring. We also expect that compared to other cleavages, race should be more likely to lead to in-group victimization in response to offshoring, whereby individuals perceive their identity group as more likely to be harmed than members of the out-group. Bringing these ideas together generates expectations over variation *within* the white sample. If we think that demand for radical political action is a response by a historically dominant identity group over its own perceived decline, then those whites who view offshoring as most harmful to other whites should also be most likely to demand (i) political action in the first place, and (ii) more radical populist policies, specifically.

7. The most common means of assessing the strength of white identity is to ask respondents to self report how important their race is to them. The ANES question employed by Jardina (2019), and others, reads: “How important is being white to your identity?”. As Jardina (2019, 69) herself points out, this formulation leaves itself open to social desirability bias, whereby some may be less willing to say that they identify strongly with their racial group. This bias may be especially present for more educated individuals. Consistent with this concern is the finding that when an interviewer is non-white, white Americans are significantly less likely to report strong racial identity.

In sum, we expect that group identity mediates individuals' perception of the distributional effects of different economic shocks. The historically dominant group is more likely to view shocks that favor an out-group as also hurting their in-group. And it is those who perceive the greatest harm to their group as a result from offshoring who should be most likely to adopt populist attitudes in response, while technology-driven layoffs should have no equivalent effect.

4 Observational Evidence

The survey experiment represents the core of our analysis, yet we begin by providing some preliminary evidence using observational data. We use the 1996-2016 waves of the ANES data to explore how layoffs affect populist attitudes among people whose occupation exposes them to automation and offshoring. We are particularly interested in any differential effect of layoffs for those exposed to automation versus offshoring. In line with our theory, we then take a first step in measuring whether racial identity affects the response to layoffs, and how this relates to vulnerability to offshoring versus automation.

4.1 Data

The bulk of the data come from the ANES Restricted Data Access (RDA). In particular, we rely on restricted geocoding of every respondent's county, which allows us to merge ANES data with layoffs data at the county level. These come from the Quarterly Workforce Indicators (QWI), collected and managed by the US Census Bureau. Moreover, we merge data on exposure to automation and offshoring at the individual level using respondents' occupation. Data on exposure to automation and offshoring come from Autor and Dorn (2013) and Blinder (2007), respectively. Our final dataset covers (up to) 597 counties and the following ANES waves: 1996, 1998, 2000, 2004, 2008, 2012, and 2016.

Our two main independent variables are the share of layoffs per worker at the county level,⁸ and variables capturing exposure to automation⁹ and offshoring¹⁰ at the individual level. Ideally, we would

8. We employ the county-level working population in the 1990 to avoid post-treatment bias.

9. The exposure to automation variable is based on the Routine Task Intensity (RTI) score from Autor and Dorn (2013). To obtain the measure, we average over all the subsidiary occupation codes matched with a respondent's ANES occupation code (71 until 2004, 97 in 2008 and 2016, 28 for web respondents in 2012) and we weight the average by occupational employment shares from the Bureau of Labor Statistics (BLS) Occupational Employment Statistics (OES) Survey.

10. This is an average of Blinder's 0-100 offshorability index (from Blinder (2007)) over occupations matched with a respondent's ANES occupation code and weighted by employment shares (based on the BLS OES Survey) in matched

like to distinguish between layoffs due to automation versus offshoring, and measure how each one affects respondents differently. Yet since data on the source of layoffs is not available, we interact county-level layoffs with individual-level vulnerability to automation and offshoring. The identifying assumption is that layoffs, which hit different counties with different intensity, trigger a differential demand for populism, depending on the type of economic vulnerability faced by respondents. A third independent variable of interest captures racial identity. In keeping with the theory, we distinguish between non-Latino whites and all other respondents.

Our outcome variable measures populist attitudes. It is an additive index of four statements/questions included in the various ANES waves: 1) “How much of the time do you think you can trust the government in Washington to do what is right?”; 2) “Public officials don’t care much what people like me think.”; 3) “Do you think that quite a few of the people running the government are crooked, not very many are, or do you think hardly any of them are crooked?”; and 4) “Would you say the government is pretty much run by a few big interests looking out for themselves or that it is run for the benefit of all the people?”.

4.2 Empirical strategy

Our main model specification is the following:

$$Y_{ic,t} = \alpha_0 + \beta_1 Automation_{i,t} + \beta_2 Offshoring_{i,t} + \beta_3 Layoffs_{c,t} + \beta_4 Automation_{i,t} \times Layoffs_{c,t} + \beta_5 Offshoring_{i,t} \times Layoffs_{c,t} + \beta_6 \mathbf{X}_{i,t} + \beta_7 \mathbf{X}_{i,t} \times Layoffs_{c,t} + \delta_c + \tau_t + \epsilon_{ic,t}, \quad (1)$$

where $Y_{ic,t}$ is our measure of populist attitudes, whereas $Automation_{i,t}$ and $Offshoring_{i,t}$ and their interaction with $Layoffs_{c,t}$ are the main independent variables. The key coefficients of interest are β_4 and β_5 , which we expect to be positive, with $\beta_4 < \beta_5$. $\mathbf{X}_{i,t}$ is matrix of controls at the individual level (age, education, gender, ideology, income, marriage status, religion, and working status). We also interact these individual-level controls with layoffs. δ_c denotes county fixed effects, and τ_t survey wave fixed effects. We run OLS regressions with robust standard errors clustered on county, and we weigh all estimations to correct for sample bias.

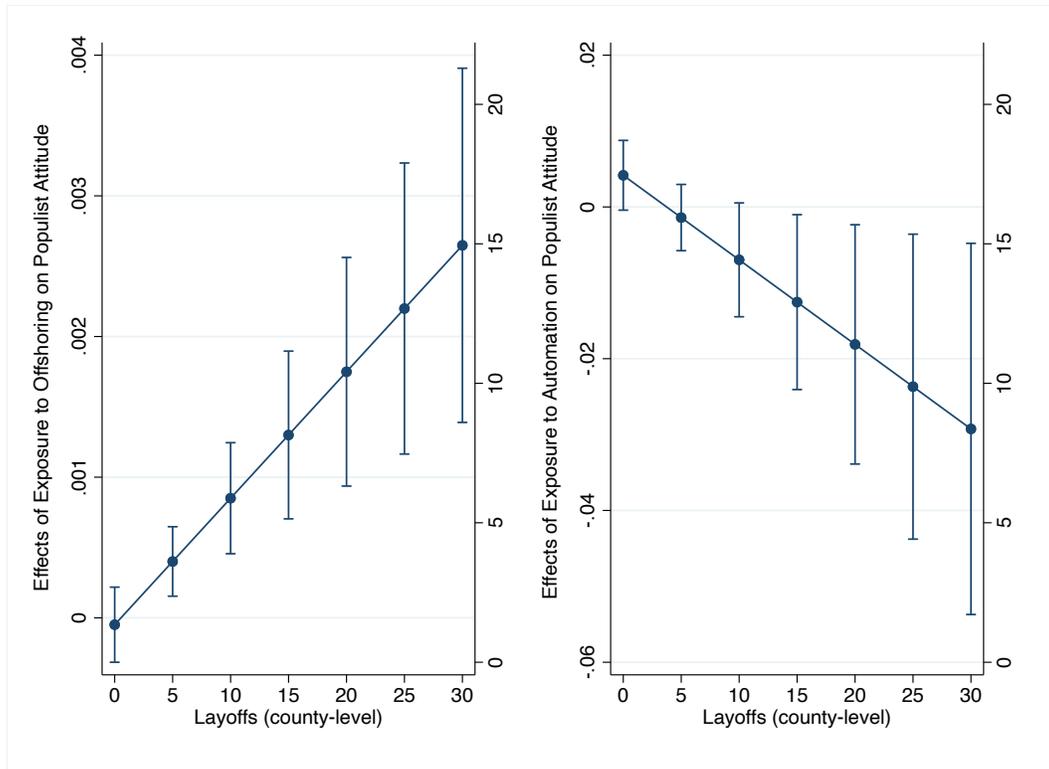
To test the differential effect between white and non-white respondents, we split Equation 1 by occupation codes.

racial identity. We show that our results are similar using triple interaction terms, whose interpretation is less intuitive. We also interact layoffs and the two economic vulnerability variables with a dummy that scores one for the 2004-2016 period to test whether the effects differ between time periods.¹¹

4.3 Results

We report the interaction effects graphically,¹² beginning with the results for the white sample in Figure 1. The marginal effect of *Exposure to offshoring* on populist attitudes is about zero in counties with very few layoffs (see left panel). By contrast, the marginal effect of *Exposure to offshoring* on populist attitudes becomes positive and significant in counties in which more than 2 percent of workers are laid off. The effect is quite substantive. Moving from a share of 5 percent laid off workers to 10 percent increases populist attitudes by about 50 percent.

Figure 1: The white sample (ANES analysis)



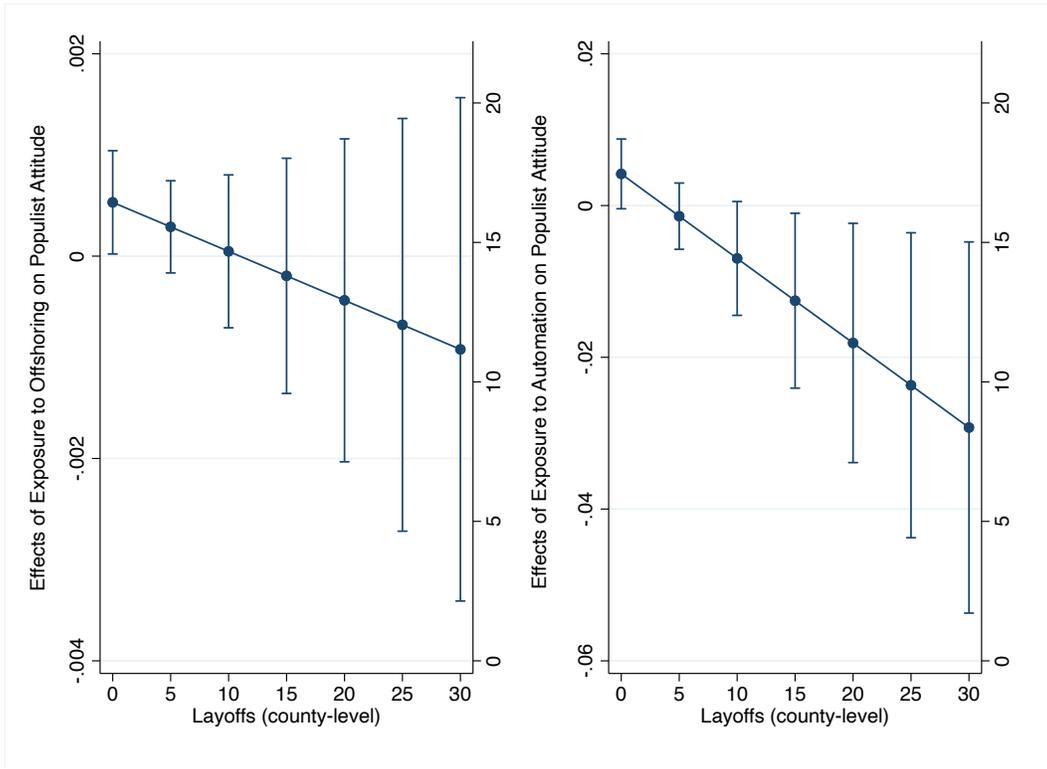
Note: Plot based on estimates from Model 1 in Table A.1.

The effect is the opposite when we plot the marginal effect of *Exposure to automation* (Figure 1,

11. 2004 is the first ANES wave after the China trade shock. Results are similar if we use 2008 or 2012.

12. Results are reported in Table A.1 in Appendix A.

Figure 2: The non-white sample (ANES analysis)



Note: The plot is based on Model 2 in Table A.1.

see right panel). Indeed, here the slope of the marginal effect is negative, indicating that as layoffs increases, individuals exposed to automation appear less likely to hold populist attitudes. The effect is significant, though of smaller magnitude than that of *Exposure to offshoring*.

Figure 2 shows results for the non-white sample. Here, individuals exposed to both offshoring and automation are less likely to hold populist attitudes in counties with a large number of layoffs. The effect is stronger for *Exposure to automation* than for *Exposure to offshoring*.

Overall, relying on observational data, white workers appear more likely to respond to offshoring than to automation. They respond to local layoffs by adopting populist attitudes when they are vulnerable to offshoring, but not automation. This difference does not obtain for non-white respondents: there, we find no differential effect on populist attitudes of offshoring versus automation. These results are confirmed when we run a triple interaction *Layoffs*, *Exposure to offshoring*, and *White* and between *Layoffs*, *Exposure to automation*, and *White*.¹³ We find no evidence that these effects are stronger in

13. Figures A.1 and A.2 report the effect of the triple interaction term in Appendix A. They are based on Model 3 in Table A.1.

recent years than in the 1990s: the interaction with the post-2004 dummy is not significant.¹⁴

In sum, the observational analysis provides preliminary evidence that whites react to offshoring-induced layoffs differently from automation-induced layoffs, compared to non-whites. We now move on to the experimental test of our theory to get a better sense of what this difference comes down to.

5 Experimental Evidence

We conducted an original survey through the survey firm *Respondi*, which collected data from a non-probability-based but nationally representative online sample—in terms of age, employment status, gender, and region¹⁵—of the US adult population.¹⁶ The survey was conducted from December 9th, 2021 to January 7th, 2022.¹⁷ The key part of the survey involves a vignette experiment, shown in Table 1. We employ simple random assignment for this between-subjects pre-registered experimental design.¹⁸

5.1 Outcome variables

Two outcome variables capture the demand for radical political action. As described above, and building on recent literature, we distinguish between *Thin populism*, which is an anti-establishment and people-centric attitude and *Thick populism*, which captures “substantive policy dimensions” (Neuner and Wrátil 2020) related to challenges to liberal democratic values.

We construct our *Thin populism* variable by averaging approval scores about the type of leader respondents see as being best-suited to addressing the economic shock: i) a political outsider; and ii) a politician who listens to the people. Similarly, our *Thick populism* variable is constructed by averaging approval scores for three response items: i) a politician who understands that using force is sometimes required to bring about positive change; ii) a politician who does not feel constrained by the rules to serve people’s needs; and iii) a politician who does whatever it takes to help their local

14. Results are reported in Table A.1 (Models 4 and 5) in Appendix A.

15. The sample is also representative of the US adult populations in terms of race/ethnicity (Whites vs. Non-whites)—see descriptive statistics in Appendix B.4.

16. On how the sample matches up with these key demographics of the US adult population, see Appendix B.1.

17. We discuss more about the study and its ethical considerations in Appendix B.3.

18. The study was pre-registered: the anonymized pre-analysis plan is available at https://osf.io/s9cqj/?view_only=db33bd8841c449ae832938afc2ac6641.

Table 1: The wording of the vignette experiment

Imagine the following event: 1,000 employees of a company in your area are being laid off because: *[randomized order, one scenario out of three]*

- the company is moving its production abroad.
- new technology is replacing human workers.
- the company is going bankrupt.

How much do you agree with the following statement (*0 - Completely disagree, 10 - Completely agree*):

It is the role of political leaders to prevent layoffs due to:

- a company moving its production abroad?
- new technology replacing human workers?
- a company going bankrupt?

[one scenario, matching the randomly assigned scenario]

On a scale where 0 means the worst and 10 means the best, which leader would be best at preventing layoffs like these? *[randomized order]*

- An experienced politician.
- A political outsider.
- A politician who listens to the experts.
- A politician who listens to the people.
- A politician who strictly follows the rules to serve people’s needs.
- A politician who does not feel constrained by the rules to serve people’s needs.
- A politician who condemns violence under any circumstance.
- A politician who understands that using force is sometimes required to bring about positive change.
- A politician who does everything they can to keep partisan divisions from splitting the nation apart.
- A politician who does whatever it takes to help their local constituents, even if it upsets other people in the country.

constituents, even if it upsets other people in the country. Both variables are measured on a 0-10 scale, with higher scores indicating greater agreement. In the Appendix, we also present results with each of the five items as the outcome.

5.2 Independent variables

Table 1 lists the three scenarios respondents are randomly assigned to: 1) offshoring; 2) automation; and 3) bankruptcy. The latter serves as our baseline, such that our treatments become *Automation* and *Offshoring*.

To get at respondents’ underlying reasoning, we ask them to guess how many of 1,000 workers in their area being laid off due to bankruptcy, offshoring, and automation are likely to be: (i) women (as opposed to men); (ii) non-white (as opposed to white); (iii) without a college degree (as opposed to with a college degree); and (iv) employed in services (as opposed to manufacturing). Here, all respondents are asked about all three layoff scenarios, yielding within-respondent variation.

We collect standard socio-demographic and political data on age, sex, region, education, residence

type, race, occupational status, ideology, political interest, partisanship, and vote in the 2020 US presidential elections. Descriptive statistics for all key variables are presented in Appendix B.4.

5.3 Empirical strategy

Our baseline model specification is the following:

$$Y_i = \alpha_0 + \beta_1 Automation_i + \beta_2 Offshoring_i + \epsilon_i, \quad (2)$$

where the outcome variable Y_i is one of the two measures of populism which we observe for each respondent i . $Automation_i$ and $Offshoring_i$ are randomized treatments, which vary across respondents. β_1 and β_2 are the key coefficients, which we expect to be consistently positive, i.e., increasing the demand for populist leaders. We expect that $\beta_1 < \beta_2$, given our reasoning about the greater political potency of offshoring. The baseline category is the scenario of layoffs due to bankruptcy. Since our outcome variables range between 0-10, we estimate OLS regressions with robust standard errors. To increase the precision of our estimates, we then add individual-level pre-treatment controls and our battery of individual-level demographics controls.¹⁹

6 Results

6.1 Baseline findings

We report our baseline findings in Table 2, where we uncover two main *causal* effects. First, offshoring is significantly more likely to trigger a demand for thick populism than automation and bankruptcy (Models 3 and 4). While the coefficient of *Offshoring* is large and significant, the coefficient of *Automation* is close to zero and not significant. The magnitude of these effects is not trivial: the *Offshoring* treatment makes respondents more favorable to radical political action by about five percent (Model 4). Secondly, automation and offshoring appear no more likely to trigger a demand for thin populism than bankruptcy (Models 1 and 2). The coefficients of *Offshoring* and *Automation* are positive, but not significant. A possible explanation is that the mean value of thin populism for the baseline bankruptcy condition is high (6.3 on a 0-10 scale) and especially high for the “listens to the people” component

19. For evidence of balance checks for key socio-demographic variables across the experimental conditions, see Appendix B.2.

(7.8). In other words, thin populist attitudes may be so high on average that it becomes difficult to observably move respondents on this dimension. This is in line with previous research showing that such populist attitudes are highly prevalent across the American political system (Bonikowski and Gidron 2016). Furthermore, the results are consistent with recent work exploring the differential impact of thin vs. thick populism on vote choice (Neuner and Wratil 2020; Silva et al. 2022), which finds that thick, ideological positions mattered more than thin populist appeals.

Table 2: Main estimations - the impact of economic shocks on radical political action

	Thin Populism (1)	Thin Populism (2)	Thick Populism (3)	Thick Populism (4)
Offshoring	0.075 (0.071)	0.065 (0.071)	0.213*** (0.083)	0.218*** (0.082)
Automation	0.070 (0.071)	0.060 (0.071)	0.044 (0.081)	0.061 (0.081)
Constant	6.263*** (0.050)	6.150*** (0.121)	5.014*** (0.059)	4.863*** (0.137)
$p(\beta_{\text{Offshoring}} = \beta_{\text{Automation}})$	0.94	0.95	0.034	0.047
Controls	No	Yes	No	Yes
Observations	3505	3505	3505	3505

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 10): Thin populism - models 1-2; Thick populism - models 3-4. The bankruptcy vignette is the reference category.

In sum, our baseline analysis offers evidence that offshoring has a causal effect on extreme populist attitudes, whereas automation has a negligible impact on the demand for radical political action.

6.2 Perceptions of in-group harm

In explaining the differential effect of automation and offshoring on the demand for populism, our argument focuses on the (perceived) differences in the costs and benefits of these two economic shocks across identity groups. To assess this component of our argument, we interact our two treatments from above with respondents' beliefs about who is most likely to be affected by layoffs due to offshoring/automation/bankruptcy. Respondents are thus asked to guess what proportion of workers affected by a given layoff type are white vs. non-white, women vs. men, non-college educated vs. college educated, and from manufacturing vs. service industries.²⁰ We then insert an interaction be-

20. The full question for the offshoring shock reads: "Imagine the following event: 1,000 employees of a company in your area are being laid off because a company is moving its production abroad. Of the 1,000 employees laid off because the company is moving its production abroad: How many would you guess are non-white?".

tween these beliefs and the treatment into Equation 2, with thin and thick populism as the outcomes of interest.

Before presenting these findings, we offer two relevant pieces of descriptive evidence. First, we estimate how likely each respondent is to (over)estimate the harm of a given type of layoff on their own racial group, gender, education category, and industry—what we refer to as “in-group victimization”.²¹ We then regress each respondent’s guess on the respondent’s own socio-demographic group. This allows us to compare the level of in-group victimization between race and the three other identity cleavages. Results are showed in Figure 3.²²

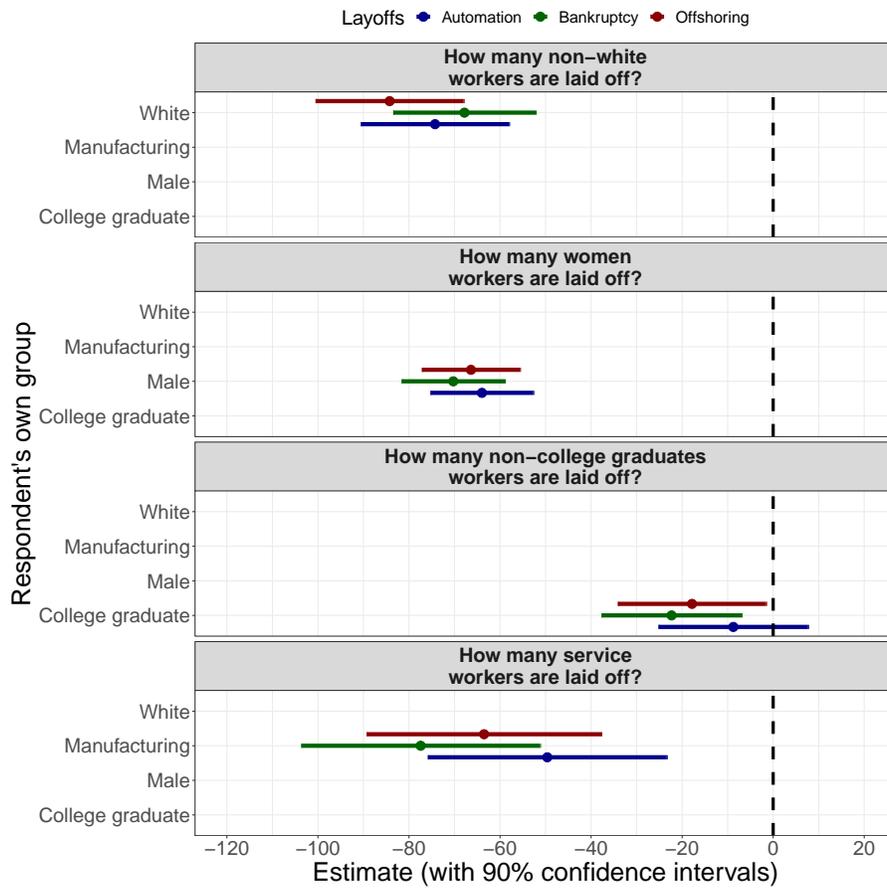
Overall, we find that the tendency towards in-group victimization is omnipresent. White Americans think that whites are the hardest hit by bankruptcy, offshoring, and automation; non-whites think the same of non-whites. Gender shows the same pattern: when asked to guess the proportion of women affected by the average layoff, men consistently guess a significantly smaller number than do women. Similarly, college graduates guess that a smaller number of non-college graduates are hit by all types of layoffs, compared to the estimates of non-college graduates. Finally, the same is true of industry: those employed in the manufacturing industry underestimate the number of layoffs that hit service workers, compared to the guesses of service workers. Yet the racial cleavage is distinctive. It is the one for which the difference between offshoring and bankruptcy, which is the baseline category, is the largest among the four cleavages. And the magnitude of in-group victimization for the combination of race and offshoring is the largest of all. In sum, respondents believe that offshoring has a disproportionately negative effect on their racial group, compared to all other identities.

Ultimately, beliefs such as these are outcomes as much as they are covariates. Yet to offer some sense of who is most likely to overestimate the proportion of white workers harmed by offshoring, Table 3 regresses a range of individual-level characteristics on the in-group victimization around race. In line with the literature on American identity politics, we find that white, older, rural, and male conservatives working in manufacturing, and who hold more nationalist views are more likely to overestimate the proportion of white workers affected by an offshoring event. While these findings hold for both offshoring and automation, the size of the coefficient is consistently larger for offshoring than for automation, with the one exception of ideology, where liberals tend to guess that non-whites

21. Figure B.1 in the appendix reports the correlation among the beliefs questions.

22. Table B.4 in the appendix presents the results of this analysis.

Figure 3: In-group victimization



Note: The figure shows respondents' guesses of how many in their identity group are affected by layoffs due to offshoring versus automation versus bankruptcy. Y-axis shows respondent identity. The plot is based on models from Table B.4 (Appendix B).

are even more affected by automation than by offshoring.

Table 3: How many non-white workers are laid off due to the economic shock?

	Guesses non-whites offshoring layoffs (1)	Guesses non-whites automation layoffs (2)
White	-56.23 (10.57)***	-50.28 (10.55)***
Big city residence	46.65 (8.47)***	44.22 (8.76)***
Female	43.12 (8.38)***	33.63 (8.52)***
Age under 36	31.22 (10.12)***	26.90 (10.19)***
Region (South)	21.48 (8.35)**	17.49 (8.48)**
Liberal ideology	19.35 (11.73)*	40.21 (11.87)***
Manufacturing job	-33.27 (14.13)**	-40.18 (14.82)***
Nationalism	-19.28 (4.28)***	-16.16 (4.30)***
Constant	384.77 (18.91)***	405.01 (19.23)***
Observations	2930	2930

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 1000): Guesses about the number of non-whites affected by offshoring - model 1; Guesses about the number of non-whites affected by automation - model 2.

We now move onto our main test. Table 4 interacts the beliefs questions with our treatments. The interaction between *Offshoring* and *Non-white affected by offshoring* is negative and significant for both thin and thick populism. This finding implies that those respondents who believe that non-whites are mostly affected by offshoring are *less* likely to demand radical political action. The equivalent effect for automation is not significant. All the interactions of the other beliefs questions are also insignificant, except for the interaction between *Offshoring* and *Service workers affected by offshoring*, where $p < 0.1$ (but only for the thin populism outcome - Model 1).

Figure 4 illustrates the effect of the interactions between *Offshoring* and *Non-white affected by offshoring* and *Automation* and *Non-white affected by automation*. The positive effect of offshoring on radical political action is driven by those respondents who believe that offshoring has a negative effect on (mostly) white workers. By contrast, the marginal effects are flatter in the case of automation, indicating that for white respondents, the impact of automation on thick populism is *not* moderated by the same considerations on the costs borne by whites.²³

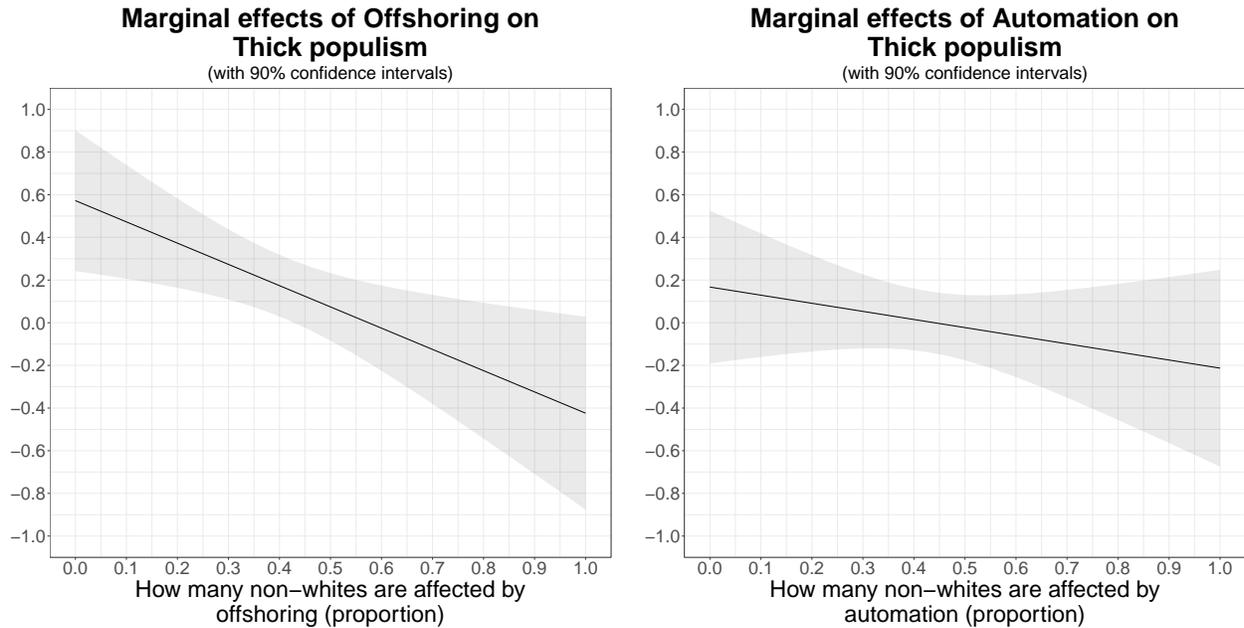
23. Figures B.2-B.4 in the appendix report the interaction effects of the other beliefs questions. Figure B.5 in the appendix investigates whether the distributional effects of shocks on race explain the demand for thin populism and the marginal effects plots reveal a much muted response compared to thick populism.

Table 4: Do beliefs about distributional consequences of shocks on identity groups explain the demand for populism?

	Thin Populism (1)	Thick Populism (2)
Offshoring * Non-whites affected by offshoring	-0.811** (0.392)	-0.996** (0.441)
Automation * Non-whites affected by automation	-0.229 (0.390)	-0.380 (0.467)
Offshoring * Women affected by offshoring	0.170 (0.453)	0.543 (0.530)
Automation * Women affected by automation	0.257 (0.450)	-0.041 (0.531)
Offshoring * Non-college graduates affected by offshoring	0.242 (0.300)	-0.455 (0.336)
Automation * Non-college graduates affected by automation	-0.331 (0.322)	0.039 (0.350)
Offshoring * Service workers affected by offshoring	-0.510* (0.297)	-0.045 (0.351)
Automation * Service workers affected by automation	-0.231 (0.309)	-0.026 (0.373)
Offshoring	0.344 (0.218)	0.586** (0.258)
Automation	0.301 (0.207)	0.173 (0.237)
Non-whites affected by offshoring	0.032 (0.259)	0.651** (0.305)
Non-whites affected by automation	-0.253 (0.275)	0.206 (0.331)
Women affected by offshoring	-0.056 (0.303)	-0.502 (0.364)
Women affected by automation	0.256 (0.297)	-0.261 (0.354)
Non-college graduates affected by offshoring	-0.160 (0.188)	-0.089 (0.207)
Non-college graduates affected by automation	0.353* (0.206)	-0.449** (0.226)
Service workers affected by offshoring	0.173 (0.200)	0.334 (0.238)
Service workers affected by automation	0.406** (0.199)	0.150 (0.245)
Constant	5.978*** (0.145)	5.116*** (0.183)
$p(\beta_{\text{Offshoring}} = \beta_{\text{Automation}})$	0.86	0.12
Controls	No	No
Observations	3037	3037

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 10): Thin populism - model 1; Thick populism - model 2. The bankruptcy vignette is the reference category.

Figure 4: Do beliefs about distributional effects of shocks on race explain the demand for thick populism? (based on model 2 in Table 4)



6.3 Additional evidence

We implement some additional tests, which we report in the appendix. First, to probe the validity of our treatments, we show that both automation and offshoring are more likely to trigger a demand for government intervention than bankruptcy—see Table B.5 in the appendix. While both effects are significant, the coefficient for *Offshoring* is about twice as large as for *Automation* (Models 1-2). These results are in line with Di Tella and Rodrik (2020). Note that these effects are *not* driven by respondents who are already in favor of redistribution as captured by pre-treatment questions (Models 3-4), suggesting that we are able to manipulate respondents’ preferences with our treatments.

Second, we show that our results are *not* driven by those who were strongly against globalization: see Table B.6 (Models 3-4) in the appendix. This represents additional evidence that our experimental manipulation was able to move respondents’ attitudes in the expected direction.

Third, we run our main models for each component of thin and thick populism: see Table B.7 in the appendix. Results show that the magnitude of the coefficient *Offshoring* is consistently larger than the magnitude of the coefficient *Automation* for all the components of thick populism. On the contrary, the difference in magnitude of coefficients is much smaller for the components of thin populism.

7 Conclusion

Forty years ago, the economist James Ingram offered an inspired economic allegory. A young entrepreneur opens a factory that runs on technology that is so advanced that it hardly requires any human workers. The entrepreneur is hailed for their inventiveness and contribution to the national economy, until a journalist exposes the truth: the factory was merely outsourcing production abroad and importing the result back into the US. Following this revelation, the entrepreneur is roundly condemned for betraying the common good by destroying US jobs.

Ingram’s allegory has only become more relevant over the last four decades: technology-driven labor displacement and offshoring have both increased in importance—though automation remains responsible for far more job losses. Economically speaking, whether jobs are displaced because of automation or trade should matter little: consumers gain in each case through access to cheaper goods, and the redundant labor can be reallocated to other tasks. Similarly, from the standpoint of individuals who lose their jobs, it should not matter whether the cause is technological progress or foreign workers.

Why might offshoring prove more politically potent than automation, even as we know that automation is responsible for more job losses overall? Our central claim is that individuals view economic shocks through the lens of group identity, and it is these refracted beliefs that account for the political effects of some shocks over others. Specifically, we argue that the difference comes down to perceptions around which groups gain and lose. Offshoring is distinctive in this respect because it benefits an identifiable out-group, foreign workers, in ways that automation does not. This aspect of offshoring should prove most relevant to members of the historically dominant group—in the case of the US, white Americans—who now perceive themselves to be losing to ascendant out-groups in demographic, economic, and cultural terms.

It is generally accepted that populism in the US is a predominantly white phenomenon. Yet the literature on identity politics also emphasizes how all members of a group do not relate evenly to their group identity. Accordingly, we expect that the more individuals believe their group is affected by offshoring, the more favorable they should be to populist political messaging in response to layoffs. Conversely, beliefs about the distributional effects of automation across identity groups should have less of an effect, because automation does not awaken the same type of group anxiety.

Our analysis combines observational and experimental evidence in support of this account, beginning with suggestive evidence from geo-coded responses to the ANES. We demonstrate that workers vulnerable to offshoring are more likely to adopt populist attitudes following real-world layoffs in their county, compared to workers vulnerable to automation. Yet this effect is unique to white workers; non-white workers react no differently to offshoring vs. automation.

To investigate the underlying mechanism, we turn to experimental data. We first show that a randomized offshoring treatment is indeed associated with populist attitudes to a greater extent than automation. Yet this baseline result conceals a great deal of heterogeneity. To unpack this variation, we evaluate individuals' relationship to the various identity groups they belong to. We ask respondents to guess the impact of offshoring vs automation on various identity groups, across race, gender, education, and industry type. While the tendency towards what we call "in-group victimization" is omnipresent, the combination of race and offshoring appears distinctive: respondents believe that offshoring has a disproportionately negative effect on their racial group, compared to other types of economic shocks and other identity cleavages. These beliefs are associated with the demographic traits that the American politics literature would lead us to expect: white, older, rural, and male conservatives working in manufacturing, and holding more nationalist views are thus most likely to overestimate the proportion of white workers affected by an offshoring event.

In our main contribution, we then show that it is these beliefs over the distributional effects of economic shocks that are most predictive of populist attitudes—but once again, only in response to offshoring. That is, the more individuals believe their racial identity group is affected by offshoring layoffs, the more favorable they are to politicians who are willing to undermine the rule of law, who remain open to the use of force, and who abet divisiveness between Americans. In sum, the findings confirm that offshoring awakens such strong political passions because it awakens latent concerns around the relative standing of identity groups. Automation is less politically potent, because it does not pit group identities against one another in the same fashion. This is why politicians often denounce competition from international trade, while they rarely condemn technology, even if it leads to considerable labor displacement.

These findings hold important implications for the common portrayal of the "white working class" in the media, political discourse, and academic scholarship. The available evidence suggests that non-white workers have been equally affected by the economic shocks of the last two decades. So why is the

white working class invariably tagged as the group that has lost from deindustrialization? Our results suggest that this may be due to how economic shocks are read through the lens of group identity. In particular, a subset of white Americans perceive losses of the same magnitude as more deleterious for their group. As a result, they become more likely to respond to these shocks by shifting their political allegiances in dramatic fashion, as illustrated by the 2016 American presidential elections. In other words, the greater political response of one group to similar economic decline has drawn disproportionate attention, which itself has shaped the public narrative. Our findings demonstrate how such public perceptions form in the first place, by identifying the individual-level beliefs that fuel them. When economic shocks are refracted through the lens of group identity, some become more politically potent than others, attracting greater attention from scholars and policymakers alike.

References

- Acemoglu, Daron, and Pascual Restrepo. 2018. The race between man and machine: Implications of technology for growth, factor shares, and employment. *American Economic Review* 108 (6): 1488–1542.
- . 2020. Robots and jobs: evidence from US labor markets. *Journal of Political Economy* 128 (6): 2188–2244.
- Anelli, Massimo, Italo Colantone, and Piero Stanig. 2021. Individual vulnerability to industrial robot adoption increases support for the radical right. *Proceedings of the National Academy of Sciences* 118 (47): 1–8.
- Autor, David, and David Dorn. 2013. The growth of low-skill service jobs and the polarization of the US labor market. *American Economic Review* 103 (5): 1553–97.
- Autor, David, David Dorn, and Gordon Hanson. 2013. The China Syndrome: Local Labor Market Effects of Import Competition in the United States. *American Economic Review* 103 (6): 2121–2168.
- Autor, David, David Dorn, Gordon Hanson, and Kaveh Majlesi. 2020. Importing political polarization? The electoral consequences of rising trade exposure. *American Economic Review* 110 (10): 3139–83.
- Baccini, Leonardo, and Stephen Weymouth. 2021. Gone for good: Deindustrialization, white voter backlash, and US presidential voting. *American Political Science Review* 115 (2): 550–567.
- Ballard-Rosa, Cameron, Judith Goldstein, and Nita Rudra. 2022. Trade as villain: The fading American dream and declining support for globalization. *Journal of Politics*.
- Ballard-Rosa, Cameron, Amalie Jensen, and Kenneth Scheve. 2022. Economic decline, social identity, and authoritarian values in the United States. *International Studies Quarterly* 66 (1): 2286–2320.
- Ballard-Rosa, Cameron, Mashail Malik, Stephanie Rickard, and Kenneth Scheve. 2021. The economic origins of authoritarian values: Evidence from local trade shocks in the United Kingdom. *Comparative Political Studies* 54 (13): 2321–2353.

- Benguria, Felipe. 2020. The impact of NAFTA on US local labor market employment. *Working paper*.
- Bisbee, James, Layna Mosley, Thomas Pepinsky, and Peter Rosendorff. 2020. Decompensating domestically: the political economy of anti-globalism. *Journal of European Public Policy* 27 (7): 1090–1102.
- Blinder, Alan. 2007. How many U.S. jobs might be offshorable? *CEPS Working Paper no. 142*, 1–44.
- Bonfiglioli, Alessandra, Rosario Crino, Gino Gancia, and Ioannis Papadakis. 2021. Robots, offshoring and welfare. *CEPR Discussion Paper No. DP16363*.
- Bonikowski, Bart, and Noam Gidron. 2016. The populist style in American politics: Presidential campaign discourse, 1952–1996. *Social Forces* 94 (4): 1593–1621.
- Bonomi, Giampaolo, Nicola Gennaioli, and Guido Tabellini. 2021. Identity, beliefs, and political conflict. *The Quarterly Journal of Economics* 136 (4): 2371–2411.
- Broz, Lawrence, Jeffrey Frieden, and Stephen Weymouth. 2021. Populism in place: the economic geography of the globalization backlash. *International Organization* 75 (2): 464–494.
- Chaudoin, Stephen, and Michael-David Mangini. 2021. Why populists neglect automation: The political economy of economic dislocation. *Working paper*, 1–81.
- Colantone, Italo, and Piero Stanig. 2018. The trade origins of economic nationalism: Import competition and voting behavior in Western Europe. *American Journal of Political Science* 62 (4): 936–953.
- Di Tella, Rafael, and Dani Rodrik. 2020. Labour market shocks and the demand for trade protection: Evidence from online surveys. *The Economic Journal* 130 (628): 1008–1030.
- Edsall, Thomas. 2018. Opinion: Robots Can’t Vote, but They Helped Elect Trump. *The New York Times*.
- Frey, Carl Benedikt, Thor Berger, and Chinchih Chen. 2018. Political machinery: did robots swing the 2016 US presidential election? *Oxford Review of Economic Policy* 34 (3): 418–442.
- Gallego, Aina, and Thomas Kurer. 2022. Workplace automation and digitalization: Implications for political behavior. *Annual Review of Political Science* 25 (6): 1488–1542.

- Gallego, Aina, Thomas Kurer, and Nikolas Schöll. 2022. Neither left-behind nor superstar: Ordinary winners of digitalization at the ballot box. *Journal of Politics* 84 (1): 1488–1542.
- Gidron, Noam, and Peter Hall. 2017. The politics of social status: Economic and cultural roots of the populist right. *The British Journal of Sociology* 68:S57–S84.
- Goos, Maarten, Alan Manning, and Anna Salomons. 2014. Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review* 104 (8): 2509–26.
- Gould, Eric. 2021. Torn apart? The impact of manufacturing employment decline on black and white Americans. *Review of Economics and Statistics* 103 (4): 770–785.
- Guisinger, Alexandra. 2017. *American opinion on trade: Preferences without politics*. Oxford University Press.
- Hanson, Gordon. 2021. Can trade work for workers? The right way to redress harms and redistributive gains. *Foreign Affairs* 100:20.
- Hunger, Sophia, and Fred Paxton. 2021. What’s in a buzzword? A systematic review of the state of populism research in political science. *Political Science Research and Methods*, 1–17.
- Im, Zhen Jie, Nonna Mayer, Bruno Palier, and Jan Rovny. 2019. The “losers of automation”: A reservoir of votes for the radical right? *Research & Politics* 6 (1): 1–7.
- Jagers, Jan, and Stefaan Walgrave. 2007. Populism as political communication style: An empirical study of political parties’ discourse in Belgium. *European Journal of Political Research* 46 (3): 319–345.
- Jardina, Ashley. 2019. *White identity politics*. Cambridge University Press.
- Jensen, Bradford, Dennis Quinn, and Stephen Weymouth. 2017. Winners and losers in international trade: The effects on US presidential voting. *International Organization* 71 (3): 423–57.
- Lee, Jaewook. 2021. Luddite or technophile? Understanding public support for regulating or accelerating automation. In *33rd Annual Meeting*. Society for the Advancement of Socio-Economics.
- Mansfield, Edward, and Diana Mutz. 2009. Support for free trade: Self-interest, sociotropic politics, and out-group anxiety. *International Organization* 63 (3): 425–457.

- Milner, Helen. 2021. Voting for populism in Europe: Globalization, technological change, and the extreme right. *Comparative Political Studies* 54 (13): 2286–2320.
- Müller, Jan-Werner. 2016. *What is populism?* University of Pennsylvania Press.
- Mutz, Diana. 2018. Status threat, not economic hardship, explains the 2016 presidential vote. *Proceedings of the National Academy of Sciences* 115 (19): E4330–E4339.
- Mutz, Diana, Edward Mansfield, and Eunji Kim. 2021. The racialization of international trade. *Political Psychology* 42 (4): 555–573.
- Neuner, Fabian, and Christopher Wrátil. 2020. The populist marketplace: Unpacking the role of “thin” and “thick” ideology. *Political Behavior*, 1–24.
- Norris, Pippa, and Ronald Inglehart. 2019. *Cultural backlash: Trump, Brexit, and authoritarian populism*. Cambridge University Press.
- Owen, Erica. 2020. Firms vs. workers? The political economy of labor in an era of global production and automation. *Working paper*.
- Pappas, Takis. 2019. *Populism and liberal democracy: A comparative and theoretical analysis*. Oxford University Press.
- Sides, John, Michael Tesler, and Lynn Vavreck. 2018. *Identity crisis: The 2016 presidential campaign and the battle for the meaning of America*. Oxford University Press.
- Silva, Bruno Castanho, Fabian Guy Neuner, and Christopher Wrátil. 2022. Populism and candidate support in the US: The effects of “thin” and “host” ideology. *Journal of Experimental Political Science*, 1–10.
- Wallach, Lori, and Daniel Rangel. 2021. Trade discrimination the disproportionate, underreported damage to US Black and Latino workers from US trade policies. *Public Citizen*.
- Walter, Stefanie. 2010. Globalization and the welfare state: Testing the microfoundations of the compensation hypothesis. *International Studies Quarterly* 54 (2): 403–426.
- Wu, Nicole. 2021. Misattributed blame? Attitudes toward globalization in the age of automation. *Political Science Research and Methods*, 1–18.

Online Appendix

Why Different Economic Shocks Have Different Political Effects

Appendices - Table of contents

A ANES analysis	1
B The survey experiment	3
B.1 Survey experiment demographics	3
B.2 Balance checks (experimental conditions)	3
B.3 Ethical considerations	4
B.4 Descriptive statistics (the survey experiment)	5
B.5 Correlation between the beliefs about distributional effects of shocks on identity groups	6
B.6 In-group victimization	7
B.7 Distributional effects - thick populism	7
B.8 Distributional effects - thin populism	9
B.9 Additional evidence	10

A ANES analysis

Figure A.1: Main results (county-level): Offshoring

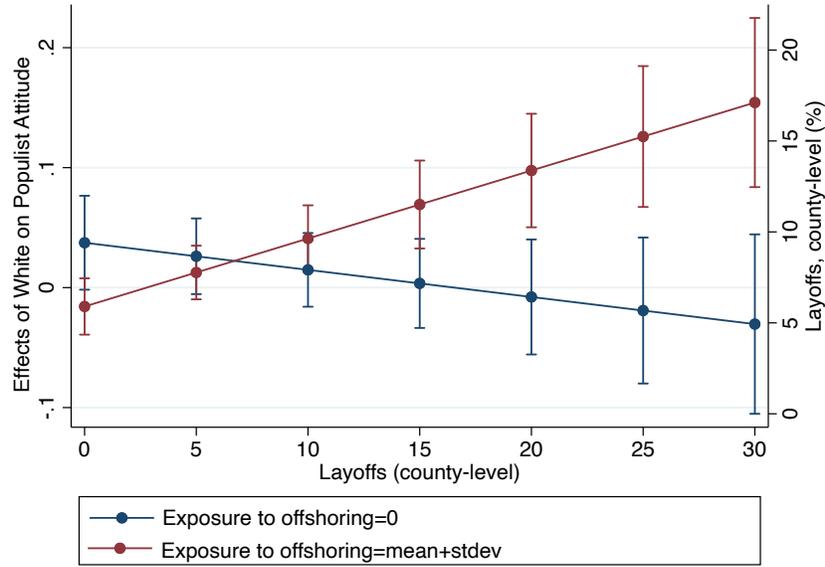


Figure A.2: Main results (county-level): Automation

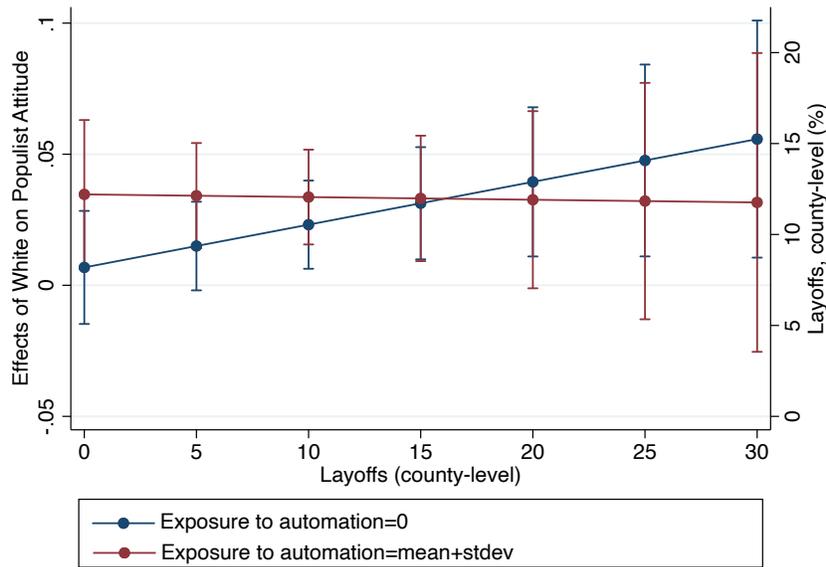


Table A.1: ANES results

	(1)	(2)	(3)	(4)	(5)
	OLS				
	Populist Attitude				
	White	Nonwhite	Full	White	Nonwhite
White			0.02968 (0.022)		
Layoff	0.00073 (0.001)	0.00009 (0.002)	0.00187 (0.001)	-0.00714 (0.007)	0.00319 (0.010)
Exposed to offshoring	-0.00005 (0.000)	0.00053* (0.000)	0.00079 (0.000)	-0.00048 (0.000)	0.00081 (0.001)
Exposed to automation	0.00417 (0.003)	-0.00128 (0.005)	-0.00658 (0.004)	0.00389 (0.005)	-0.00140 (0.011)
White*Layoffs			-0.00178 (0.002)		
White*Exposed to offshoring			-0.00097 (0.001)		
White*Exposed to automation			0.01281** (0.004)		
Layoffs*Exposed to offshoring	0.00009*** (0.000)	-0.00005 (0.000)	-0.00005 (0.000)	0.00023 (0.000)	0.00009 (0.001)
Layoffs*Exposed to automation	-0.00111** (0.001)	-0.00047 (0.001)	-0.00060 (0.000)	0.00003 (0.002)	-0.00037 (0.006)
White*Layoffs*Exposed to offshoring			0.00014** (0.000)		
White*Layoffs*Exposed to automation			-0.00080 (0.001)		
Layoffs*Exposed to offshoring*Post2004				-0.00016 (0.000)	-0.00012 (0.001)
Layoffs*Exposed to automation*Post2004				-0.00114 (0.002)	-0.00008 (0.006)
Constant	0.45268*** (0.028)	0.29542*** (0.039)	0.37600*** (0.048)	0.45541*** (0.028)	0.29494*** (0.039)
Observations	6,507	2,664	9,369	6,507	2,664
R-squared	0.166	0.161	0.132	0.167	0.163
Controls	Yes	Yes	Yes	Yes	Yes
County fixed effects	Yes	Yes	Yes	Yes	Yes
Wave fixed effects	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Note: OLS coefficients with robust standard errors clustered at the level of the county in parentheses. The unit of observation is individual-county-wave. The outcome variable measures populist attitudes with an additive index of four statements/questions included in the various ANES waves: 1) “How much of the time do you think you can trust the government in Washington to do what is right?”; 2) “Public officials don’t care much what people like me think.”; 3) “Do you think that quite a few of the people running the government are crooked, not very many are, or do you think hardly any of them are crooked?”; and 4) “Would you say the government is pretty much run by a few big interests looking out for themselves or that it is run for the benefit of all the people?” Source: *ANES, QWI, US Census Bureau*.

B The survey experiment

B.1 Survey experiment demographics

Table B.1: Survey demographics (distribution of quota variables)

Variable	Respon sample (%)	US adult population (%, 2019/2021)	Difference (%)
Sex: Male	47.40	48.70	-1.30
Sex: Female	52.60	51.30	1.30
Age: 18-24	11.00	11.80	-0.80
Age: 25-34	15.70	18.00	-2.30
Age: 35-44	16.30	16.30	0.00
Age: 45-64	34.10	32.70	1.40
Age: 65+	22.80	21.20	1.60
Region: Northeast	17.40	17.40	0.00
Region: Midwest	21.10	20.80	0.30
Region: South	38.20	38.10	0.10
Region: West	23.30	23.80	-0.50
Employment Employed	61.50	61.80	-0.30
Employment Unemployed	38.50	38.20	0.30

Note: N = 3505 (the ResponDI sample). Data sources: US Census Bureau (2019) - see indicators NC-EST2019-AGESEX (age and sex) and SCPRC-EST2019-18+POP-RES (region population) <https://www.census.gov/data/tables/time-series/demo/popest/2010s-national-detail.html>; Bureau of Labor Statistics (US Department of Labor) - employment data (2021) <https://www.bls.gov/news.release/pdf/empsit.pdf>.

B.2 Balance checks (experimental conditions)

Table B.2: Balance checks (analysis of variance) - the survey experiment

Variable	Experiment	p_value
White (Hispanics excluded)	Negative shocks	0.34
College graduate	Negative shocks	0.84
Big city residence	Negative shocks	0.48
Working	Negative shocks	0.46
Annual income under 50k	Negative shocks	0.30
Female	Negative shocks	0.93
Age under 36	Negative shocks	0.25
Region (South)	Negative shocks	0.31
Democrat	Negative shocks	0.12
Voted Biden	Negative shocks	0.15
High political interest	Negative shocks	0.67

B.3 Ethical considerations

Our research has received ethics clearance from the Research Ethics Board of [anonymized information] (REB File #: 21-01-034). Furthermore, our research adheres to the APSA Principles and Guidance for Human Subjects Research.

We conducted our original survey with Respondi. The sample was drawn from an online panel used only for market research and for which membership and participation are voluntary and follow a double opt-in registration process. The respondents were able to take the survey only after reading the consent form and agreeing to it. The consent form clearly stated key details such as the following: 1) the study was an academic survey; 2) who conducted the study and who funded it; 3) the general goal of the study; 4) how the data will be used; 5) how the subjects can end the survey at any point by simply closing their browser; 6) how the data will be protected; and 7) how the respondent can contact the Research Ethics Board or the researchers. The wording of the consent form is available in Appendix A of the pre-analysis plan (https://osf.io/s9cqj/?view_only=db33bd8841c449ae832938afc2ac6641).

The study did not involve at-risk or vulnerable populations. Our sample is representative (in terms of age, sex, region, and employment status) of the US adult population.

The study did not use deception.

The study did not intervene in the political process.

The study protects the confidentiality of the respondents. We, as researchers, did not collect data that would make the respondents identifiable.

The respondents were compensated for their work by Respondi. Specifically, each respondent received \$1 for their answers. This represents approx. 32% of the fee we paid to Respondi for an interview. The payment is in line with what other similar platforms offer to respondents.

B.4 Descriptive statistics (the survey experiment)

Table B.3: Descriptive statistics (survey experiment)

	N	Mean	SD	Median	Min	Max	SE
Prevent layoffs	3505	4.80	2.78	5	0	10	0.05
Thin populism	3505	6.31	1.73	6.50	0	10	0.03
Thick populism	3505	5.10	1.97	5	0	10	0.03
Listens to people	3505	7.78	2.06	8	0	10	0.03
Political outsider	3505	4.84	2.57	5	0	10	0.04
Unconstrained by rules	3505	4.71	2.90	5	0	10	0.05
Does not rule out force	3505	4.57	2.73	5	0	10	0.05
Accepts divisiveness	3505	6.01	2.53	6	0	10	0.04
Offshoring experimental condition	3505	0.32	0.47	0	0	1	0.01
Automation experimental condition	3505	0.33	0.47	0	0	1	0.01
Bankruptcy experimental condition	3505	0.34	0.47	0	0	1	0.01
Non-white affected by offshoring	3037	398.10	227.15	382	0	1000	4.12
Non-white affected by automation	3037	421.62	229.72	403	0	1000	4.17
Non-white affected by bankruptcy	3037	420.58	224.78	402	0	1000	4.08
Women affected by offshoring	3037	432.32	183.96	411	0	1000	3.34
Women affected by automation	3037	425.55	191.79	413	0	1000	3.48
Women affected by bankruptcy	3037	439.99	193.38	444	0	1000	3.51
Non-college graduates affected by offshoring	3037	510.22	270.08	515	0	1000	4.90
Non-college graduates affected by automation	3037	524.05	272.33	540	0	1000	4.94
Non-college graduates affected by bankruptcy	3037	495.52	252.75	500	0	1000	4.59
Services workers affected by offshoring	3037	363.95	247.89	324	0	1000	4.50
Services workers affected by automation	3037	372.63	245.43	340	0	1000	4.45
Services workers affected by bankruptcy	3037	399.53	242.98	397	0	1000	4.41
Male	3505	0.47	0.50	0	0	1	0.01
White (non-Hispanic)	3505	0.74	0.44	1	0	1	0.01
Non-college graduate	3505	0.42	0.49	0	0	1	0.01
Manufacturing	3505	0.07	0.26	0	0	1	0
Big city residence	3505	0.60	0.49	1	0	1	0.01
Age under 36	3505	0.28	0.45	0	0	1	0.01
Region (South)	3505	0.38	0.49	0	0	1	0.01
Working now	3505	0.60	0.49	1	0	1	0.01
Democrat	3505	0.36	0.48	0	0	1	0.01
Republican	3505	0.28	0.45	0	0	1	0.01
Political interest (high)	3505	0.72	0.45	1	0	1	0.01
Voted Biden	3505	0.49	0.50	0	0	1	0.01
Liberal (ideology)	3505	0.27	0.44	0	0	1	0.01
Nationalism	3505	1.37	1.05	1	0	3	0.02
Low on redistribution	3505	0.23	0.42	0	0	1	0.01
Low on globalization	3505	0.19	0.39	0	0	1	0.01

B.5 Correlation between the beliefs about distributional effects of shocks on identity groups

Figure B.1: Correlation between the beliefs about distributional effects of shocks on identity groups

Service workers affected by bankruptcy (guess)	0.25	0.31	0.34	0.24	0.31	0.38	0.25	0.29	0.31	0.56	0.61	1
Service workers affected by automation (guess)	0.23	0.27	0.28	0.25	0.34	0.29	0.21	0.25	0.23	0.63	1	0.61
Service workers affected by offshoring (guess)	0.23	0.23	0.23	0.26	0.25	0.25	0.17	0.19	0.2	1	0.63	0.56
Non-college graduates affected by bankruptcy (guess)	0.29	0.37	0.48	0.25	0.34	0.43	0.64	0.69	1	0.2	0.23	0.31
Non-college graduates affected by automation (guess)	0.34	0.48	0.39	0.28	0.4	0.35	0.68	1	0.69	0.19	0.25	0.29
Non-college graduates affected by offshoring (guess)	0.38	0.39	0.34	0.28	0.34	0.31	1	0.68	0.64	0.17	0.21	0.25
Women affected by bankruptcy (guess)	0.42	0.45	0.57	0.64	0.68	1	0.31	0.35	0.43	0.25	0.29	0.38
Women affected by automation (guess)	0.45	0.53	0.44	0.71	1	0.68	0.34	0.4	0.34	0.25	0.34	0.31
Women affected by offshoring (guess)	0.47	0.38	0.37	1	0.71	0.64	0.28	0.28	0.25	0.26	0.25	0.24
Non-whites affected by bankruptcy (guess)	0.69	0.74	1	0.37	0.44	0.57	0.34	0.39	0.48	0.23	0.28	0.34
Non-whites affected by automation (guess)	0.76	1	0.74	0.38	0.53	0.45	0.39	0.48	0.37	0.23	0.27	0.31
Non-whites affected by offshoring (guess)	1	0.76	0.69	0.47	0.45	0.42	0.38	0.34	0.29	0.23	0.23	0.25
Non-whites affected by offshoring (guess)												
Non-whites affected by automation (guess)												
Non-whites affected by bankruptcy (guess)												
Women affected by offshoring (guess)												
Women affected by automation (guess)												
Women affected by bankruptcy (guess)												
Non-college graduates affected by offshoring (guess)												
Non-college graduates affected by automation (guess)												
Non-college graduates affected by bankruptcy (guess)												
Service workers affected by offshoring (guess)												
Service workers affected by automation (guess)												
Service workers affected by bankruptcy (guess)												

B.6 In-group victimization

Table B.4: In-group victimization

	No. laid-off non-white workers offshoring (1)	No. laid-off non-white workers automation (2)	No. laid-off non-white workers bankruptcy (3)	No. laid-off women workers offshoring (4)	No. laid-off women workers automation (5)	No. laid-off women workers bankruptcy (6)	No. laid-off non-college workers offshoring (7)	No. laid-off non-college workers automation (8)	No. laid-off non-college workers bankruptcy (9)	No. laid-off service workers offshoring (10)	No. laid-off service workers automation (11)	No. laid-off service workers bankruptcy (12)
White	-84.257*** (9.888)	-74.276*** (9.893)	-67.814*** (9.511)									
Male				-66.387*** (6.551)	-63.976*** (6.862)	-70.266*** (6.887)						
College graduate							-17.824* (9.900)	-8.754 (9.983)	-22.318** (9.340)			
Manufacturing										-63.514*** (15.659)	-49.617*** (15.952)	-77.431*** (15.939)
Constant	460.689*** (8.776)	476.799*** (8.725)	470.950*** (8.312)	463.865*** (4.697)	455.947*** (4.807)	473.379*** (4.920)	520.496*** (7.487)	529.099*** (7.542)	508.384*** (7.227)	368.546*** (4.697)	376.226*** (4.645)	405.140*** (4.585)
Controls	No	No	No	No	No	No	No	No	No	No	No	No
Observations	3037	3037	3037	3037	3037	3037	3037	3037	3037	3037	3037	3037

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 1000): Number of laid-off non-white workers (offshoring) - model 1; Number of laid-off non-white workers (automation) - model 2; Number of laid-off non-white workers (bankruptcy) - model 3; Number of laid-off women workers (offshoring) - model 4; Number of laid-off women workers (automation) - model 5; Number of laid-off women workers (bankruptcy) - model 6; Number of laid-off non-college graduate workers (offshoring) - model 7; Number of laid-off non-college graduate workers (automation) - model 8; Number of laid-off non-college graduate workers (bankruptcy) - model 9; Number of laid-off service workers (offshoring) - model 10; Number of laid-off service workers (automation) - model 11; Number of laid-off service workers (bankruptcy) - model 12.

B.7 Distributional effects - thick populism

Figure B.2: Do beliefs about distributional effects of shocks on education explain the demand for thick populism? (based on model 2 in Table 4)

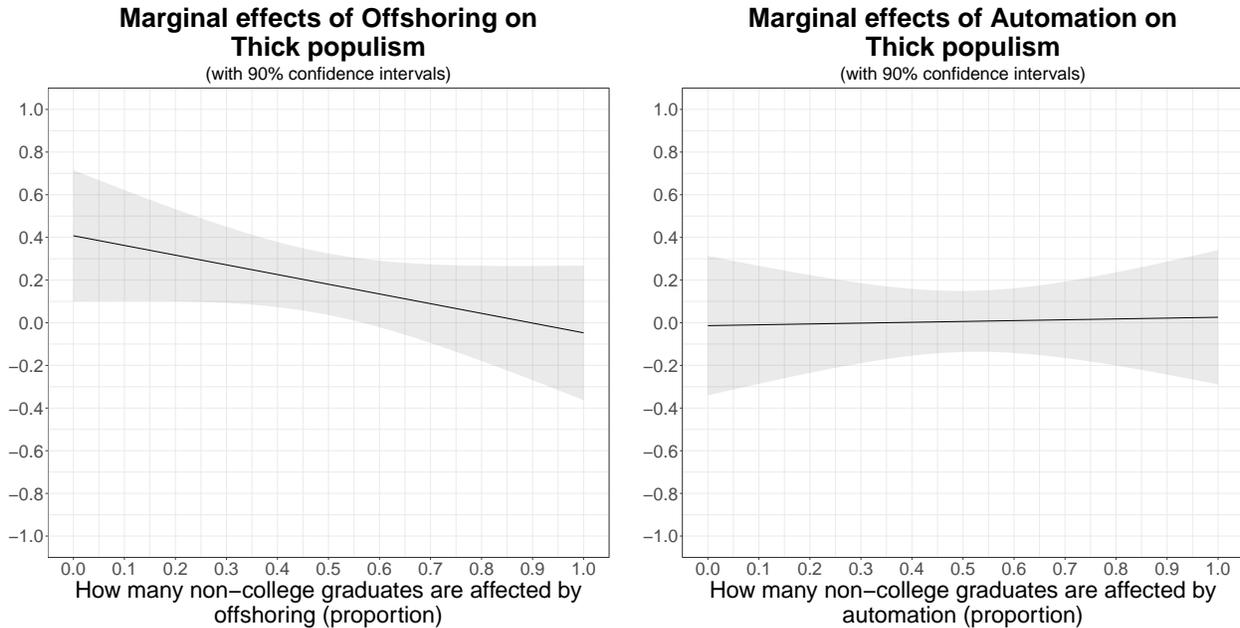


Figure B.3: Do beliefs about distributional effects of shocks on sex explain the demand for thick populism? (based on model 2 Table 4)

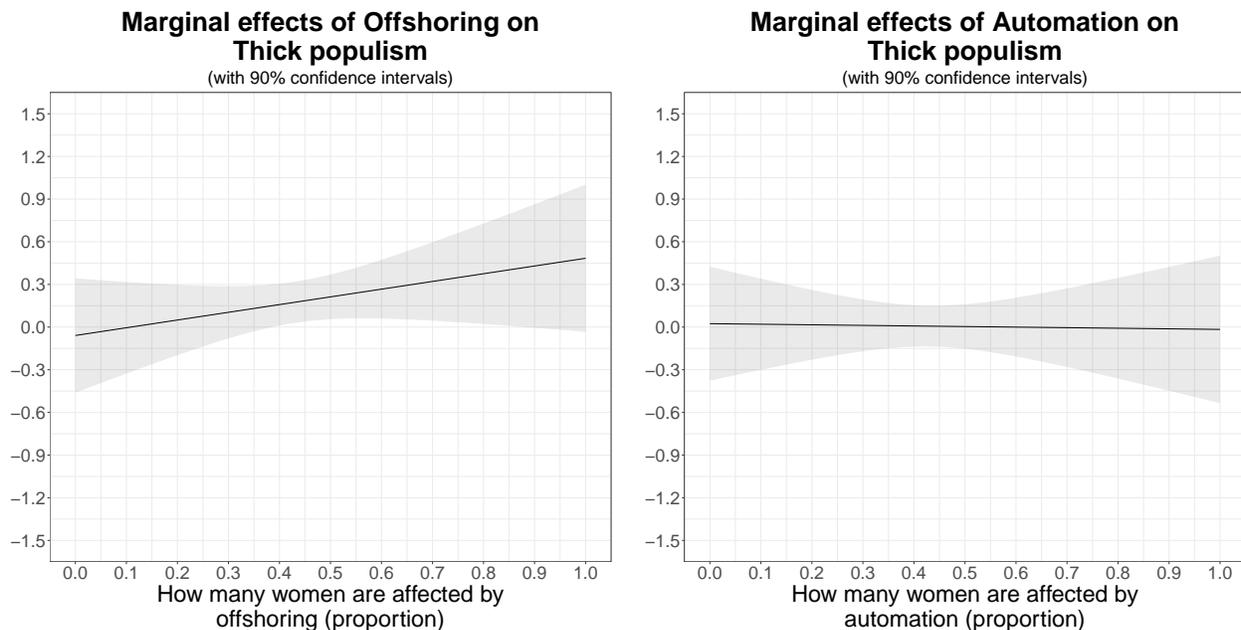
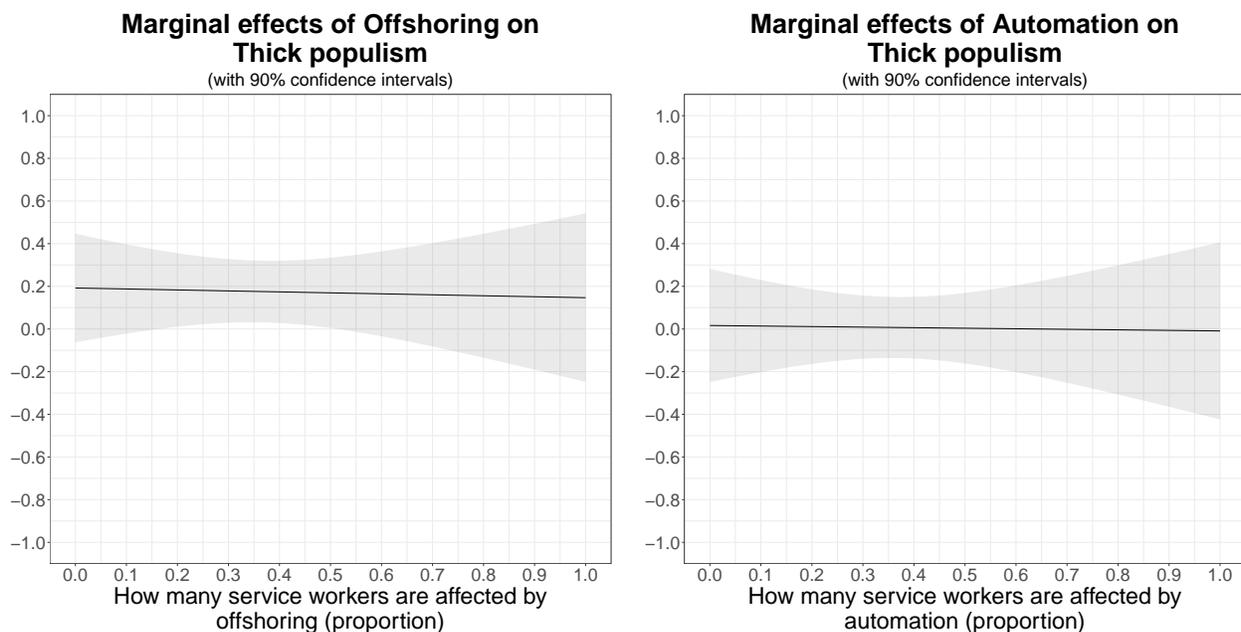
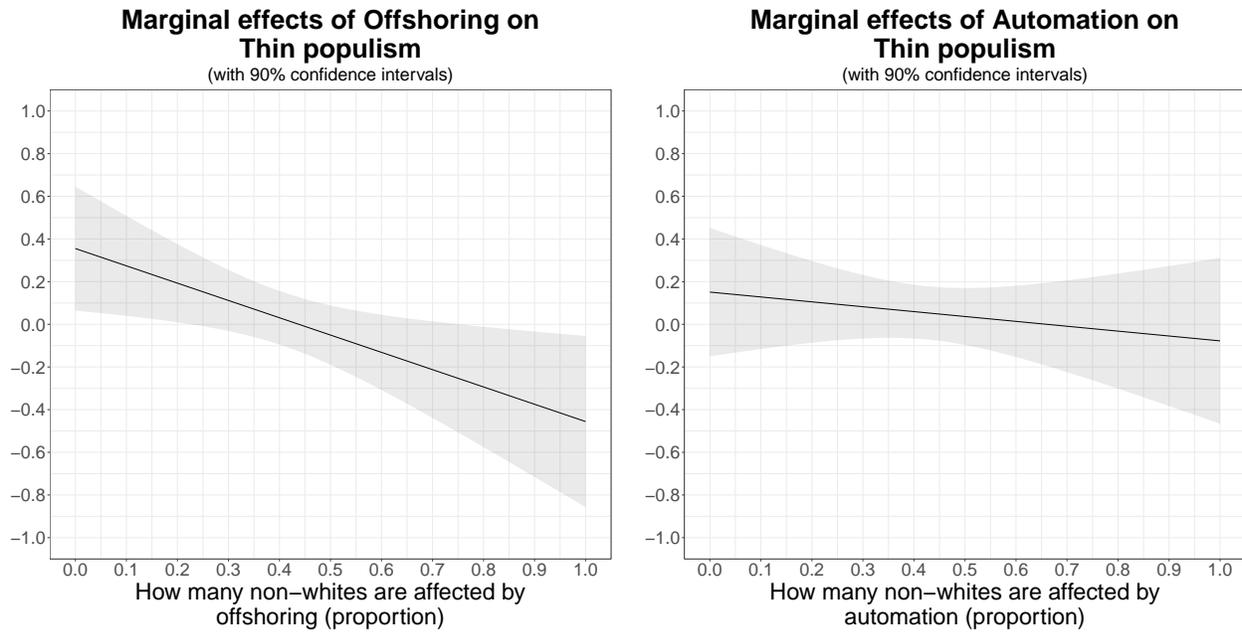


Figure B.4: Do beliefs about distributional effects of shocks on sector of employment explain the demand for thick populism? (based on model 2 Table 4)



B.8 Distributional effects - thin populism

Figure B.5: Do beliefs about distributional effects of shocks on race explain the demand for thin populism? (based on model 1 in Table 4)



B.9 Additional evidence

Table B.5: The effect of the treatments on preventing layoffs

	Prevent Layoffs (1)	Prevent Layoffs (2)	Prevent Layoffs (3)	Prevent Layoffs (4)
Offshoring	1.362*** (0.113)	1.404*** (0.110)	1.094*** (0.120)	1.107*** (0.119)
Automation	0.770*** (0.112)	0.833*** (0.108)	0.720*** (0.120)	0.755*** (0.118)
Offshoring * Low redistribution support			1.020*** (0.273)	1.025*** (0.274)
Automation * Low redistribution support			0.364 (0.245)	0.306 (0.244)
Low redistribution support			-2.532*** (0.163)	-2.382*** (0.179)
Constant	4.102*** (0.080)	3.570*** (0.184)	4.684*** (0.087)	4.336*** (0.184)
$p(\beta_{\text{Offshoring}} = \beta_{\text{Automation}})$	0.000	0.000	0.001	0.002
Controls	No	Yes	No	Yes
Observations	3505	3505	3505	3505

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 10): Politicians should prevent these layoffs - models 1-4. The bankruptcy vignette is the reference category.

Table B.6: The role of globalization

	Thin Populism (1)	Thin Populism (2)	Thick Populism (3)	Thick Populism (4)
Offshoring	0.086 (0.075)	0.073 (0.075)	0.203** (0.088)	0.210** (0.088)
Automation	0.042 (0.074)	0.035 (0.074)	0.021 (0.087)	0.044 (0.086)
Low globalization support	0.353** (0.147)	0.247* (0.149)	-0.326* (0.170)	-0.250 (0.171)
Low globalization support * Offshoring	-0.041 (0.206)	-0.022 (0.205)	0.040 (0.231)	0.023 (0.230)
Low globalization support * Automation	0.171 (0.207)	0.162 (0.206)	0.106 (0.227)	0.065 (0.225)
Constant	6.193*** (0.051)	6.062*** (0.123)	5.078*** (0.063)	4.943*** (0.139)
$p(\beta_{\text{Offshoring}} = \beta_{\text{Automation}})$	0.56	0.62	0.036	0.054
Controls	No	Yes	No	Yes
Observations	3505	3505	3505	3505

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 10): Thin populism - models 1-2; Thick populism - models 3-4. The bankruptcy vignette is the reference category.

Table B.7: Main models - individual populism items

	Listens to people (1)	Listens to People (2)	Political Outsider (3)	Political Outsider (4)	Unconstrained by rules (5)	Unconstrained by rules (6)	Does not rule out force (7)	Does not rule out force (8)	Accepts divisiveness (9)	Accepts divisiveness (10)
Offshoring	0.100 (0.085)	0.112 (0.084)	0.051 (0.106)	0.017 (0.105)	0.082 (0.121)	0.083 (0.120)	0.168 (0.114)	0.182 (0.112)	0.390*** (0.105)	0.389*** (0.105)
Automation	0.024 (0.085)	0.044 (0.083)	0.116 (0.106)	0.076 (0.104)	-0.003 (0.119)	0.009 (0.118)	-0.013 (0.113)	0.012 (0.111)	0.149 (0.105)	0.162 (0.105)
Constant	7.743*** (0.060)	7.447*** (0.143)	4.783*** (0.074)	4.854*** (0.179)	4.689*** (0.085)	4.558*** (0.199)	4.519*** (0.081)	4.569*** (0.188)	5.833*** (0.075)	5.461*** (0.180)
$p(\beta_{\text{Offshoring}} = \beta_{\text{Automation}})$	0.37	0.42	0.54	0.57	0.48	0.54	0.11	0.13	0.02	0.028
Controls	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	3505	3505	3505	3505	3505	3505	3505	3505	3505	3505

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. OLS estimations with robust standard errors in parentheses. Dependent variables (0 - 10): Politician who listens to the people - models 1-2; Political outsider - models 3-4; Politician unconstrained by rules - models 5-6; Politician who thinks force is needed - models 7-8; Politician who helps local constituents - models 9-10.