A COLLECTION OF ESSAYS ON THE BACKLASH AGAINST GLOBALIZATION, AUTOMATION, AND DEINDUSTRIALIZATION

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ABSTRACT

This dissertation investigates the structural economic underpinnings of the rise in negative identity politics in the United States, exploring the extent to which globalization, automation, and broader deindustrialization trends contribute to the rising of right-wing populism. It posits that the manufacturing sector's decline, driven by globalization and automation and other factors, has significantly reshaped the labor market, and exacerbated partisan polarization and racial divisions, particularly among the white working class. The thesis contends that the diminishing of manufacturing jobs, historically intertwined with white privilege, has sparked an identity crisis among white Americans, fueling a nostalgia for a past racial and economic order and providing fertile ground for white identity politics. As white workers often cannot identify the precise sources of their economic distress, it argues that the combined effects of deindustrialization, rather than globalization or automation alone, are more substantially linked to the rise of white identity politics. This study challenges the traditional political economy model that interprets grievances through the lens of public demand for redistribution, suggesting that white Americans' backlash against economic shocks manifests primarily in symbolic racial tensions rather than in affective partisan polarization or redistributive policies. Drawing on nationally representative survey data, the dissertation investigates the link between economic shocks and identity politics, finding evidence of a correlation between deindustrialization and racial tensions, and indicating that white Americans may be channeling their grievances into identity politics rather than seeking redistribution.

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CHAPTER 1: INTRODUCTION

Why are US politics today characterized by negative identity politics–particularly, partisan polarization and racial divisions? What are the mechanisms by which structural economic factors affect the rise of right-wing populism? I argue that deindustrialization, either from globalization or technological shock, is the main driver for negative white identity politics. Both trade shock and automation shock lead to labor market reshuffling, and because of the distributional consequences of the two, trade shock and automation shock contribute to the rise of populist politics in developed economies independently as well as working together (in the form of general deindustrialization). The existing literature adopts two political economy models to explain the link between economic shocks and populist politics: policy responses and social identity backlash. However, the evidence is mixed as to which channel is the main mechanism.

1.1 Manufacturing Jobs and White Privileges

Historically, whites in the U.S. have enjoyed a dominant position in the social hierarchy. Whiteness is associated with certain racial and job privileges. The idea of a white American identity began to take shape as European settlers distinguished themselves from Indigenous peoples and enslaved Africans, and over time, this racial hierarchy was codified into law and social practice. The post-World War II era marked a period of economic prosperity and a boom in manufacturing jobs that disproportionately benefited white Americans, particularly men—this period solidified the link between whiteness, economic opportunity, and social status.

Manufacturing jobs and white privileges are well documented in the academic literature. In his seminal work, Du Bois (1935) made a compelling observation about the white working class. He emphasized that this group often derived a sense of self-worth and identity from their racial background. They perceived their "whiteness" as not just an identity, but also as a symbol of privilege and distinction. Roediger (1999) further conceptualizes it as a “public and psychological wage”. This term can be interpreted as an intangible benefit or perceived value that doesn't come in the form of financial compensation. This "wage" is deeply rooted in social and political privileges. In simpler terms, for the white working class, there's an inherent societal value or advantage attached to their identity. This benefit is psychological because it affects how individuals perceive themselves and their place in society. It's public because it's recognized and, to an extent, validated by the broader community or societal structure. This "wage" isn't about monetary gain but about the sense of superiority, belonging, or privilege that comes from one's racial or social status. Harris (1993) elaborates on the concept of "whiteness," describing it as a "settled expectation" – a deep-seated belief or assumption. This means that, historically and culturally, being white has been associated with an ongoing and almost guaranteed advantage across various spheres, including economic, political, and social domains. Guisinger (2017) suggests that for some white Americans, manufacturing jobs are viewed as crucial, historical avenues of employment primarily for their community. In essence, this suggests that there's an ingrained societal perception that being white is often linked to having better opportunities and favorable conditions in these areas.

1.2 Deindustrialization, Social Identity Threat, and the Rise of White Identity Politics

However, as the backbone of economic stability for the white working class, manufacturing jobs have been decreasing heavily since the 1960s, especially after the 2000s, with the fast development of globalization and technological advancement. The immediate effects of all deindustrialization in local communities on workers are not only manufacturing job loss, it also affects the gender earnings gap, the marriage and fertility of male workers, and children’s household living environment (Autor et al., 2019a); the infant mortality rate (Bombardini & Li, 2016); people's mental health (Colantone et al., 2019); the overall suicide rate, accidental poisoning, and alcohol-related liver disease (ARLD) (Fort et al., 2018; Pierce & Schott, 2016, Case & Deaton, 2015). With deindustrialization, the white working class in America has experienced a profound identity shift. Communities that had once thrived on the prosperity brought by local factories and plants began to crumble as jobs were outsourced or automated, leading to widespread economic dislocation and social disarray. As the economic foundation of these communities eroded, demographic shifts further complicated the narrative. Increased immigration from Latin America and Asia, along with higher birth rates among minority populations, contributed to the decline of the white majority in the United States. The demographic profile of the US began to change markedly, and projections of a future where whites would no longer constitute a numerical majority added to the anxieties of those already disaffected by economic changes.

This sense of economic disenfranchisement along with the demographic changes activated and heightened the white identity and the racialization of American whites (Tesler, 2015). White Americans do have a racial identity in the same way that people of color do (Jardina, 2019a). A significant number of white Americans do feel strong racial solidarity and perceive themselves as part of a broader white group. The loss of manufacturing jobs, which once served as a basis of economic stability and upward mobility, has given rise to feelings of marginalization and a reorientation toward political ideologies that emphasize nationalistic sentiments (Gest, 2016). Communities that once thrived on local industries have faced social and economic disarray, propelling a politics of resentment. This sentiment reflects a broader rural consciousness that feels overlooked by a political elite perceived to favor urban interests and global economic trends over traditional American industries and lifestyles (K. J. Cramer, 2016).

Deindustrialization-caused distress and anxieties are not only individual sufferings, they are also politically salient status threats for dominant economic and social groups--in the US, the White working class. The ensuing identity-based backlash has been characterized by a nostalgic yearning for a past era of unchallenged white dominance and prosperity (Gay et al., 2016). White identity politics is not merely a backlash against the progress of other racial groups; it is also a proactive movement to preserve white cultural and political influence (Jardina, 2019b). The socio-political response has been shifting towards movements and political figures advocating for a resumption of perceived lost status and a return to the "old" social order when cultural values and racial identities aligned more closely with economic policies (For example, Trump's slogan "Make American Great Again"). This shift has seen white identity politics move from a latent undercurrent to a pronounced force in American political discourse, now shaping the nation's debates on immigration, social policy, and the collective national identity (Owens et al., 2010). This "identity crisis" has been used for the political mobilization of right-wing politics in the 2016 presidential election (Sides et al., 2018a). A prominent example of this trend is well-documented by Goldstein's (2017) book: *Janesville: An American Story*. It vividly illustrates this transition through the lens of the lives of people in Janesville, Wisconsin, a town that suffered a major economic blow when the oldest operating General Motors assembly plant in the country closed in 2008. Residents in the town not only have to grapple with immediate financial instability but also the long-term effects on their children, the community fabric, and their identity.

Although the actual effect of deindustrialization is more severe for racial minorities, whites still have a misperception that they are affected more and become the "white minorities" (Hochschild, 2018; Tesler, 2015). Thus, the whites are responding to the negative shock of deindustrialization differently from the non-whites as different social groups react differently to similar economic challenges (Baccini & Weymouth, 2021; Green & McElwee, 2019). Dominant social status threats can be manifested in the forms of negative identity politics among some whites–affective partisan polarization, and racial resentment. It is therefore understandable why some white workers are not supporting more redistribution.

1.3 The Academic Debates on Deindustrialization, Right-Wing Populism Backlashes

The decline of the US manufacturing sector has produced a lot of social, economic, and political issues. A burgeoning literature focuses on how trade shock (Acemoglu et al., 2014; D. Autor et al., 2019b, 2020a; D. H. Autor et al., 2013a, 2013b; Davenport et al., 2021) or automation shock (Acemoglu et al., 2022; Acemoglu & Autor, 2010; Acemoglu & Restrepo, 2020, 2022; Autor et al., 2003) affect the manufacturing displacement in developed democracies, especially in the US. However, scholars are still debating which of the two makes the greater contribution to manufacturing job loss. Building on these seminal works, political economists further explore the political consequences of these economic shocks, mainly motivated by the election of Donald Trump in the US, Brexit in the UK, and right-wing populism in general in Western democracies (for example, Jensen et al., 2017, (D. Autor et al., 2020a), COLANTONE & STANIG, 2018a; Colantone & Stanig, 2018b, Frey et al., 2013, Anelli et al., 2023). In this literature, scholars are debating whether it's an economic backlash (Autor et al., 2020), a cultural backlash (Norris & Inglehart, 2018, Mutz, 2021), or an economic-identity backlash (Baccini & Weymouth, 2021; Broz et al., 2021; Ballard-Rosa et al., 2022; Ballard-Rosa et al., 2021). The mechanisms through which trade/automation shock and deindustrialization in general affect right-wing populism are still not clear and not fully tested. Specifically, existing literature still cannot answer why the backlash is mainly manifested as right-wing populism, not left-wing redistribution. Individual-level evidence that leads to the "last mile politics" is also lacking (Bisbee, 2020; Bisbee & Rosendorff, 2021).

In this collection of essays, I try to bridge these gaps in the literature. I take a comprehensive approach and aim to investigate how deindustrialization–either caused by trade shock or automation shock–affects partisan polarization, racial resentment, and policy preferences. Trade shock and automation shock do not have statistically significant effects on either affective polarization or racial resentment, does that mean the most prominent phenomenon in the US, occurring at the same time as the rise of China trade shock, automation shock, are not affected at all by labor market reshuffling? The main reason that individual-level evidence is lacking is that previous studies examine trade shock or automation shock separately, instead, I argue in this chapter that deindustrialization, regardless of its sources, is the main driver for negative identity politics in the US context. In addition to examining the two main sources of deindustrialization separately and indirectly, we should also examine the whole effects and directly focus on the labor market, as voters are not always able to distinguish "which" or even "what" has caused the manufacturing layoffs, let alone forming clearly defined policy preferences and political attitudes based on their assessment of the weight of the different shocks. For example, previous research has shown that U.S. citizens often have limited knowledge about trade patterns and mechanisms, even within their nation (Rho & Tomz, 2017). In many cases, they will even misattribute the blame to one another (Gallego & Kurer, 2022; Wu, 2022, 2023). Moreover, I follow Ballard-Rosa et al., (2021, 2022) and Baccini & Weymouth (2021) in arguing that economic shock and cultural shock are not mutually exclusive, it is an economic shock of identity backlash. I complement their work by further testing the social identity mechanisms: affective polarization and racial division. Building on this, I also test how deindustrialization affects voters' policy preferences on redistribution.

1.4 Why the Focus on the Two Social Identities: Race and Partisanship?

I argue that negative identity politics are the main mechanisms that link deindustrialization and their changing policy preferences on redistribution and voting for Trump. The main motivation for the focus on racial divisions is that racial attitudes directly affect the voting for Trump and other negative politics. For example, Reny et al. (2019) find that vote switching in the 2016 presidential election is strongly associated with voters' racial attitudes. To be more specific, they find that members of the white working class with conservative views on race are more inclined to change their vote to support Trump in 2016, whether they previously identified as independents or Democrats. Moreover, race is deemed to be of vital importance in American politics. Some scholars even emphasize the "centrality of race" in American politics (Hutchings & Valentino, 2004). They find that race matters in almost all-important aspects of American politics, from "party politics, voting behavior, and policy preferences to elite behavior, democratic responsiveness, and political communication" (Hutchings & Valentino, 2004).

The focus on affective polarization is motivated by the fact that it is a defining feature of the current US politics (Druckman et al., 2021). This concept was first developed by (Iyengar et al., 2012a) based on the social distance concept (Bogardus, 1947). It is the feeling of distance, i.e. the level of emotional and identity animosity, between the two-party members. They argue that affective polarization can better capture the group affiliation aspect of party identification. Ideological and even identity per se cannot fully capture the in-group and out-group dynamics. They argue that the definition of social identity should not only capture the positive effect on in-group candidates and members but should also capture the negative sentiment towards out-groups. Therefore, this affective polarization is not necessarily consistent with policy positions. While it is well documented and widely accepted that elite polarization is increasing significantly in the

US, mass ideological polarization is still under debate. Most findings suggest that people are not becoming ideologically more extreme than before (Druckman & Levendusky, 2019; Frieden, 2019; Iyengar et al., 2012b). However, mass partisan polarization based on the conception of social identity has sound empirical evidence (Iyengar et al., 2019). (D. Autor et al., 2020b) already test how trade shock-led trade shock contributes to the rise of elite polarization and individual ideological polarization. But the individual-level evidence on the more fundamental partisan polarization–affective polarization is still lacking.

1.5 A Social Identity Theory of Deindustrialization and White Identity Politics

Social identity theory (SIT) is the main theory that can explain how labor market reshuffling could lead to negative white identity politics. There are four specific mechanisms based on SIT: the dominant social status threat theory, the frustration-conformity and frustration-aggression mechanism, the anxiety-thus-certainty-seeking mechanism, and scapegoating.

The dominant social group in this case is the white in the US. Workers in manufacturing-heavy communities will face huge pressure from deindustrialization from trade shock: from low wages to unemployment and other unwanted social consequences. These negative consequences not only pose threats to the affected individuals' everyday lives but also lead to the perception that the group's esteem as the once-privileged white working class is under serious threat. As a dominant social identity almost always involves privileges (Doane, 1997; McDermott & Samson, 2005), if members of the dominant social groups lost their privileges due to social economic changes, they would feel the threat as a whole group, not only as an individual. In other words, it is a question of social esteem so much as self-esteem. Gidron & Hall (2020) propose the concept of social integration to explain how well individuals integrate into society. They argue it is based on three criteria: a) if one is in a "*shared normative order*"; b) if they have good "*social* *interactions*"; c) if they feel "*respected*" or "*recognized*" by others. Deindustrialization and the ensuing unwanted consequences would influence all three aspects of white workers. There are plenty of in-depth field studies on how the white working class feels. For example, Hochschild (2018) conducted thorough fieldwork in one deep-red state in the Southern US. Her immersion in the Tea Party supporter communities in the American South reveals the angry emotions of the conservatives. They feel they are lost; they are forgotten by the Washington insiders and the liberal mainstream media. They feel like they are "strangers on their own land". Gest (2016) goes even further, using surveys and full-immersion fieldwork, he finds that the dominant white working class does not feel they are the dominant anymore, they feel they are the "new minority". Although the perception is not fully based on facts, their feeling of status loss of the white working class is more than real. The "*fear of falling*" even further down the social ladder would make them draw distinctive social boundaries between the "respectable" selves and those with less social standings like racial minorities (Gidron & Hall, 2020). The direct threat to the white working-class identity is the non-white racial minorities. Before it can go further to affect other social identities.

The threat of deindustrialization along with the demographic change that the white is losing their majority gradually also means that those white workers affected by economic hardship will require *conformity* and *submission* from minorities to compensate for their status loss (Baccini & Weymouth, 2021; Ballard-Rosa et al., 2021a, 2022). However, that compensation is never possible anymore in a globalized world, as liberal and more progressive principles become widely accepted. As the dominant white group, they're accumulating their animosity toward these minorities. The social status threat and individual economic frustration can also incentivize aggression tendencies from affected white workers. Building on the seminal work on authoritarianism (Adorno, 1950; Ballard-Rosa et al., 2021a, 2022) argue that deindustrialization, specifically trade shock from

China would make the dominant social group–in this case, the whites in the US– become more *conventionalism* and generate more *aggression* to out-groups.

Relatedly, labor market reshuffling can cause rising levels of insecurity, anxiety, uncertainty, and even anger among once-privileged social groups as well as minorities. It is what I call the anxiety-thus-certainty-seeking mechanism. It suggests that the heightened economic shock from manufacturing job loss could increase people's anxiety, insecurity, and uncertainty about their economic prospects and social standing in the future. On the individual level, affected individual workers are increasingly becoming certainty-seeking (Hogg, 2000, 2007, 2014; Hogg et al., 2012). Uncertainty is associated with anxiety-related emotions. These emotions can make people feel unsure about their behavior of themselves, and the behavior of others. But not all uncertainties are relevant in the process, only those aspects that are important to our life can provoke anxiety and stress that need us to give more cognitive energy to resolving it. People always face uncertainty, there is no way that a person can achieve absolute certainty (Dewey 1929 cited in Hogg et al., 2017). People will not always deal with uncertainty. But suppose the uncertainty is about oneself, relationships, and the future and the uncertainty are accompanied by anxiety, fear, or a sense of helplessness. In that case, it will create a strong motivation for us to allocate energy to deal with it. The most effective way for people in a society to reduce uncertainty is through group identification. Based on social identity theory (Turner et al., 1979), people can use social groups to define their self-concept. The self-categorization theory says people will reinforce intragroup feelings and intergroup feelings when seeking certainty (Hogg & Turner, 1987). The process will educate us on how to behave as a group member of a certain group compared with another group. Hogg et al. (2017) argues that although all groups help reduce group members' uncertainty, not all groups have the same effects. The most important group identity must have “*entitativity*”, namely, the group with clear boundaries. In addition to the previous characteristics, the above group tends to have “*essentialism*”—that is, people will perceive it to be enduring and permanent. Partisanship and racial identity are the two most politically salient social identities in the US. White workers seeking certainty may strengthen their identification with their white working-class roots and lean towards political parties that align with their values. Similarly, minority groups might reinforce their racial identities and lean towards political parties that address their specific concerns for redistribution. This mechanism is most prominent when there are extreme conditions that create acute uncertainty (Hogg et al., 2017). For example, natural disasters, economic recessions, governmental reform, war unemployment, divorce, etc. are extreme conditions that can create a higher level of uncertainty. Moreover, not only does uncertainty reinforce intragroup closeness and similarity, but it will also lead these members to direct emotions, values, and attitudes towards out-group members.

The final mechanism is scapegoating. When facing all the challenges of deindustrialization, people will try to find “someone to blame” (Bauer et al., 2023; Bursztyn et al., 2022a, 2022b). On the supply side, some politicians might use the cleavages to mobilize support by adopting antiminority, and anti-establishment narratives (Rodrik & Kennedy, 2018; Voigtländer & Voth, 2015). Building on the classic literature, (Bursztyn et al., 2022a) further argue that the latent animosity toward out-groups can be activated in times of economic crisis, as it can give intolerant people a “*rationale*” for their discriminating views with less social backlashes. In normal good times, latent “haters” would not publicly express their biased views as it is frowned upon and against mainstream values. Although Bursztyn and his coauthors do not distinguish instant economic hardship from long-term economic hardship like trade shock and automation shock, the effect should be the same. The long-term economic decline from import competition would gradually embolden these latent "haters" to publicly express their antipathy toward other groups as more and more people from their group are affected by the structural change from import competition. Therefore, long-term trade shock should gradually contribute to the expression of negative attitudes toward out-groups.

1.6 The Plan of this Dissertation

The empirical analysis tests how trade shock, automation shock, and manufacturing layoffs affect affective polarization, racial resentment, and attitudes toward liberal policies among whites in the US. Using nationally representative survey data from the 2008 National Annenberg Election Study (NAES), the American National Election Studies (ANES) 2012 and 2016 waves, and the Cooperative Election Study (CCES) 2016 wave. The empirical analysis tests whether local labor market reshuffling–measured as a 20-year-change trade shock from China on the commuting zone level, automation shock on the commuting zone level, and a 4-year shift-share change of manufacturing jobs on the county level(Baccini & Weymouth, 2021), affect individual-level identity politics, thus examining the mechanisms that localized deindustrialization affect the rise of right-wing populism in the US. It mainly focuses on white people as the theory is a theory of "white backlash" to deindustrialization. Following previous literature, this chapter also adopts Bartik (1991) instrumental variable research design.

The rest of the dissertation is structured as follows: the first chapter focuses on whether trade shock alone can trigger enough identity backlashes among whites in the US. The second chapter examines automation shock and white identity backlashes. The third chapter adopts a comprehensive approach to test deindustrialization as a whole on the white backlashes in the US. The final chapter concludes with discussions on policy implications and future research questions.

CHAPTER 2: TRADE SHOCK, IDENTITY POLITICS, AND PUBLIC SUPPORT FOR LIBERAL POLICIES

2.1 Introduction

Does import competition from trade affect the negative identity politics in the US? Specifically, does trade shock have any impact on partisan affective polarization in the US? Does trade-related economic hardship have any influence on racial attitudes in the US? Does trade shock have any impact on the public support for liberal policies?

2.1.1 A Brief History of US Trade Policy after World War II

After World War II, the United States, recognizing the drawbacks of protectionism that exacerbated the Great Depression, led efforts to establish a more open and predictable global trading system. This led to the creation of the General Agreement on Tariffs and Trade (GATT) in 1947, which aimed at reducing barriers to international trade through the gradual reduction of tariffs, quotas, and subsidies. Throughout the Cold War, U.S. trade policy focused on bolstering free trade as a means of countering the spread of communism, by integrating economies and fostering alliances through commerce. By the 1970s, the economic dominance of the U.S. began to wane as Japan and Western Europe recovered. The oil crises and concerns about trade deficits led to more protectionist measures, such as "Voluntary Export Restraints" on Japanese cars. From the 1980s to the early 2000s, there was a significant move towards trade liberalization. The North American Free Trade Agreement (NAFTA), which created a free-trade zone between the U.S., Canada, and Mexico was signed in the 1990s. The GATT transformed into the World Trade Organization (WTO) in 1995, with the U.S. as a founding member, which introduced more comprehensive trade rules and a mechanism for resolving trade disputes. China had been granted accession to the WTO in 2001 and the trade with China surged afterwards.

However, the rapid rise of China's economy and its admission into the WTO in 2001 led to increased competition for U.S. manufacturers and a growing trade deficit. The aftermath of the 2008 financial crisis and concerns over trade imbalances led to a resurgence of protectionism. The Trump administration, starting in 2017, marked a significant departure from previous policies by imposing tariffs on imports from China, leading to a trade war, and renegotiating NAFTA to create the United States-Mexico-Canada Agreement (USMCA). There was also a withdrawal from the TPP and a critical stance towards the WTO. Though less aggressive, the Biden administration has also emphasized a review of existing trade agreements, enforcing trade rules to protect American industries, and a focus on competing with China.

2.1.2 Trade Shock from China and Deindustrialization in the US

Trade shocks from China have huge impacts on the US labor markets. The amount of U.S. consumer spending on Chinese products in 1991 was only 0.06 percent of the total spending, but in 2007, it had already grown to a significant 4.6 percent (Autor et al., 2013b). This growth notably picked up speed after China became a member of the World Trade Organization (WTO) in 2001. Concurrently, the percentage of the U.S. working-age population with jobs in manufacturing dropped significantly, declining from 12.6 percent to 8.4 percent. The seminal research by Autor et al. (2013a) shows a significant employment reduction in U.S. regions most exposed to trade with China between 1990 and 2007. A rise of $1,000 in import exposure from China is associated with a decline of 0.60 percent in manufacturing employment in those affected regions. The impact is not mitigated by intersectoral employment shifts or geographical migration, with the latter found to be notably infrequent in response to trade shocks (Autor et al., 2013b). In the same vein, (Acemoglu et al., 2016) attribute approximately 10% of the decline in U.S. manufacturing jobs to

Chinese import competition, with a ripple effect resulting in an estimated total of 2 million job losses across various sectors from 1999 to 2011.

The repercussions extend beyond job loss. Trade shocks also depress wages, increase the likelihood of plant closures, and reduce tax revenue, affecting local public services and housing markets (D. H. Autor et al., 2016; Feler & Senses, 2017). There's also evidence of wider social implications, such as deteriorating mental health and increased mortality rates due to substance abuse and suicide, particularly among white males (Case & Deaton, 2015; Fort et al., 2018b). These factors contribute to declining male social status relative to females, as reflected in shrinking gender earnings gaps and adverse effects on family formation and stability (Autor et al., 2019a).

2.1.3 The Academic Debate on "The Backlash Against Globalization"

The growing body of research on "the backlash against globalization" focuses on the rise of populism, particularly right-wing populism, in the voting patterns within advanced economies, while noting that left-wing populism is more prevalent in developing regions like Latin America (Rodrik, 2018). Scholars are engaged in a robust debate over the origins and even the reality of this backlash. Three main theoretical explanations have emerged: the first posits that economic shocks spur the backlash; the second challenges the notion of a backlash against globalization or suggests that if it exists, it stems not from economic causes but from clashes in cultural values and identities; and the third seeks a middle ground, suggesting that economic self-interest and social identities are intertwined, collectively shaping voter attitudes and actions.

The varied reactions to trade shocks—ranging from shifts in cultural values and issue attitudes, such as the demand for redistribution, to changes in political behavior like voting or activism—are diverse (Bisbee & Rosendorff, 2021). To understand recent political upheavals like Trump's election, Brexit, and the rise of right-wing parties in OECD nations, it's essential to consider how prolonged economic disturbances might fundamentally alter voter perceptions and social identities. Notably, negative identity politics play a significant role in the current backlash within developed economies. While prevailing research acknowledges the importance of negative social identities, it often fails to empirically test whether trade shocks intensify the prominence of racial identity or partisan polarization, two key social identities in the U.S. Moreover, the literature tends to focus more on the "outcome significance"—the effects of these backlashes—rather than the "explanatory significance"—the underlying causes. There is also a scarcity of individual-level data that could elucidate the "last mile politics" leading to these political shifts (Bisbee & Rosendorff, 2021). Margalit (2019) criticizes this approach, arguing that conflating the impact of economic insecurity and populism with its explanatory strength can be misleading. While trade shocks may play a role in the rise of populism and hence hold "outcome significance," they do not always provide explanatory insight into the specific success of right-wing populism. In sum, the literature often overlooks the mechanisms at play in these backlash narratives.

2.1.4 Plan of Chapter One

In this chapter, I explore the impact of trade shocks on individual-level social identities that hold political weight, such as racial attitudes and partisan affective polarization, as well as the resulting views on economic redistribution. I propose that in the United States, trade shocks may significantly influence right-wing populism through the activation of negative white identity politics. There are two principal ways this connection may manifest. Firstly, it works through the social identity theory, which can be broken down into four sub-mechanisms: the hypothesis of dominant status threat, scapegoating or diversion, anxiety due to uncertainty, and authoritarian conformity and aggression. Secondly, the trade shock's effects could also be mediated through policy responses, particularly those concerning economic redistribution.

The empirical part tests how trade shock from China on the commuting zones affects racial resentment, partisan affective polarization–defined as the animosity between Democrats and Republicans in the US, and attitudes toward several liberal policies on redistribution. There are two main findings. Firstly, trade shock does not have a significant effect on racial attitudes, partisan affective polarization, or public support for liberal policies among whites. In other words, trade shock alone cannot explain the regional variation of negative identity politics. Secondly, the social identity theories previous studies rely on do not have individual-level evidence.

This research makes contributions to at least three important literatures: the negative identity politics literature, the redistribution literature, and the economic shock and the backlash against globalization literature. This chapter examines whether long-term economic change from trade has any direct effect on negative identity politics, contributing to the growing literature on the political economy of negative identity politics in the US context. It also examines how social identity cues; especially racial cues might affect attitudes on liberal policies for trade shock-affected white workers. Last but not least, it tests the main causal mechanism through which trade shock can be translated to right-wing populism vote shares.

The rest of the paper is structured as follows: the second section reviews the literatures on trade shock and negative politics. The third part lays out the theoretical framework of how trade shock might affect negative identity politics and related views toward liberal policies. The following part discusses the instrumental variable research design. The fifth part shows the results of the estimation. The final part concludes by discussing some of the limitations and implications of the findings. The main data are from the 2008 National Annenberg Election Study (NAES) and 2016 CCES.

2.2 Literature Review

Two academic debates are related to the topic of this chapter. The first debate is on whether the China trade shock is the main driver for the right-wing populism backlash. The second debate is on whether trade policy preferences align with people's self-interest.

2.2.1 The Debate on the China Trade Shock

Scholars are still debating the backlash against globalization. One strand of the theory argues that the rise of populism is a backlash against globalization, especially trade shock. The first line of studies mainly focuses on economic shock, especially economic globalization (such as trade) as the main cause for the rise of right-wing populism.

Since the seminal work of Autor et al. (2013a) on China (trade) shock, a lot of studies have documented the negative impacts of trade shock on the labor markets (Acemoglu et al., 2012, 2016; D. Autor, 2021; D. Autor et al., 2020b; Broz et al., 2021; Feler & Senses, 2017), and related serious social consequences in the US (Bombardini & Li, 2016; Case & Deaton, 2015; COLANTONE & STANIG, 2018; Colantone & Stanig, 2018c, 2019; Fort et al., 2018b; Pierce & Schott, 2016). These negative consequences could lead to the white workers' attitudes change before they are accumulated to the aggregate level of collective action–the rise of right-wing populism politics in the form of voting. Utilizing congressional roll-call data, Feigenbaum & Hall (2015) highlight the influence of China's trade shocks on U.S. legislators' voting behaviors. Such shocks led to a preference for protectionist trade bills, especially in districts with threatened incumbents, though other bill votes remained unaffected. In a related vein, (Jensen et al., 2017) noted that U.S. presidential elections saw reduced incumbent vote shares due to Chinese imports, while exports bolstered them. Expanding the focus to the European context, (Dippel et al., 2015) find that trade shocks in Germany specifically boosted extreme-right parties, with manufacturing labor market adjustments playing a key role. (Colantone & Stanig, 2018c, 2018a, 2018b) find that UK regions hit harder by Chinese imports leaned towards Brexit and revealed a broader rightward shift across fifteen Western European countries from 1988 to 2007, marked by growing support for nationalist and radical-right factions.

A second line of work questions the backlash against globalization theory and argues that economic globalization does not contribute to the rise of populism, even if there is a backlash because the backlash is not solely focused on economic policies, it instead should be a cultural backlash (R. F. Inglehart et al., 2016; Mutz, 2018, 2021a; Norris & Inglehart, 2018; Rothwell & Diego-Rosell, 2016) or an identity crisis with the white Americans lose their dominance due to demographic changes over time (Jardina, 2019b; Mutz, 2018; Sides et al., 2018a). Inglehart et al. (2016) suggest that the backlash against globalization is not purely economically driven, as is often assumed. Instead, they argue that the rise in populism can be largely attributed to a cultural backlash. This cultural backlash emerges from a deep-seated tension between progressive societal changes and more traditionalist or conservative attitudes. In societies where rapid cultural change has happened, such as shifts in values or norms, there might be a segment of the population that feels left behind or alienated. Thus, these individuals could be drawn to populist movements as a form of resistance against these progressive changes, rather than a direct response to economic grievances related to globalization. Rothwell and Diego-Rosell (2016) contribute to the discussion by delving into the nuances of the backlash, suggesting that it isn't entirely about economic policies. Their study finds that many who support populist movements or ideas do not always do so because of direct economic grievances. Instead, there are other underlying factors, such as cultural anxieties, that play a more significant role. Mutz (2018) offers a similar perspective, suggesting that the association between globalization backlash and populism isn't as clear-cut as it seems. In her work, she touches upon both the cultural backlash theory and the influence of dominant group status threat. The latter refers to the anxiety dominant racial or ethnic groups might feel when they perceive their societal dominance to be under threat. In the case of the U.S., this translates to white Americans feeling that their dominant position is being challenged by demographic changes, leading to support for populist ideas or movements. Sides (2019) and his colleagues build on the concept of dominant group status threat. Their research indicates that white Americans' perceptions of losing their societal dominance due to demographic changes have been a significant factor in the rise of certain populist movements and sentiments. This sense of perceived threat is fueled by a combination of racial and identity dynamics, rather than strictly economic concerns linked to globalization. Jardina (2019) also centers her work around the notion of white identity politics in the U.S. She posits that as demographic changes become more pronounced and visible, many white Americans begin to see their group's dominance as under threat. This perceived threat to white identity and dominance is a potent force that can drive support for populist movements and figures.

A third line of works tries to settle the debate by combining the economic shock theories with the social identity theories. Without disputing the identity theories, they add a layer of economic shock factors to it. Specifically, Autor et al. (2020) focus on import competition and issue polarization. They argue that trade shock from China leads to electing more extreme candidates in Congress for both liberals and conservatives in the US. They cite several theoretical models for explaining the co-occurrence of trade protectionism and identity politics. Their main theoretical explanation is from (Grossman & Helpman, 2018, 2021) who build a formal model arguing that adverse economic shocks like the trade shock may trigger both a psychological response and a material interest response. The psychological response will strengthen group identification, and the material interest response is manifested in their preference for trade protectionism. Ballar-Rosa et al. (2021a, b) argue that long-term trade-related economic changes hurt “the social identity of historically dominant groups”. They examine their argument in the US context and argue that white voters’ fear of the loss of their dominant social status will incentivize them to enforce more conformity and social order from minority out-groups like blacks and Latinos. They further argue that this requirement for conformity is contingent on the local level of race proportions. Since a white majority area would have fewer opportunities to encounter nonconformist behavior of out-group members. In the same vein, Baccini and Weymouth (2021) argue whites and blacks have different responses to economic shocks resulting from deindustrialization in the US, and that some white people in the US, shocked by deindustrialization, might feel a loss of the conventional relative higher social status while blacks won’t think so. To cope with identity loss and maintain the hierarchy, some whites might favor candidates who could help address their concerns. That’s why whites in the affected areas will favor Republican candidates while blacks will favor Democrats.

Although the works assume that trade shock leads to a negative psychological response that strengthens group identifications, they do not specify the working mechanism. Moreover, individual-level evidence is still lacking for the negative responses other than voting.

2.2.2 The Debate on Individual Trade Policy Preferences and Self-interest

The debate over whether trade preferences reflect economic self-interest is that while economic self-interest is a significant factor in shaping individuals' trade preferences, it is not the sole driver. Non-economic factors such as cultural identity, psychological predispositions, and political affiliation also play crucial roles, suggesting a complex interplay between various determinants that goes beyond the traditional models of economic self-interest. Classical political economy theories and factor endowment models traditionally suggest that individuals favor trade policies aligned with their personal economic interests, as seen in the works of Hufbauer (1974), who argued that individuals' positions on trade—whether for liberalization or protectionism—correlate with their roles within the economy. Supporting this, Scheve & Slaughter (2001) indicated that higher-skilled workers tend to support free trade due to the benefits they receive from globalization, whereas lower-skilled workers may oppose it due to competition concerns.

However, this straightforward correlation is contested by scholars who consider additional influences. (Mansfield & Mutz, 2013) introduce the idea that societal norms and ideological beliefs often have a stronger influence on trade preferences than economic self-interest. This is echoed by Hainmueller & Hiscox (2006), who suggest that education can override economic self-interest in shaping trade attitudes. Rho & Tomz (2017) show that an individual's stance on trade is not merely a reflection of how they personally benefit or suffer economically but is also significantly influenced by the signals and positions adopted by political leaders and parties with which the individual identifies. Their research delves into the cognitive processes behind trade policy attitudes, illustrating that people often lack detailed knowledge about the complexities of trade and its impacts on the economy. This lack of expertise prompts individuals to rely on heuristic shortcuts to form opinions on trade policies, heavily leaning on their political identities and the cues they receive from trusted partisan sources. For instance, if a political party or leader that an individual trusts endorses a free trade agreement, the individual is more likely to view the agreement favorably, regardless of their economic situation.

2.3 Theoretical Framework

2.3.1 Trade Shock, Deindustrialization, and White Identity Politics

Trade shocks are significant drivers of deindustrialization, affecting the local labor markets and thereby exerting a profound influence on white identity politics through the framework of Social Identity Theory. The white working class, once the bedrock of the U.S. industrial sector, perceives a stark loss of privilege and social esteem as trade-induced labor market reshuffling leads to job losses and economic instability. This perceived threat to their dominant status and the attendant economic insecurities catalyze a retreat to more rigid in-group identities, often expressed through heightened political and racial solidarity. The resulting behaviors are shaped by four distinct mechanisms: a dominant social status threat leading to increased group cohesion; a conformity and aggression response fueled by frustration; an anxiety-driven search for certainty that strengthens group affiliations; and scapegoating, where out-groups are blamed for economic woes. Politicians might exploit these dynamics, adopting narratives that stoke anti-minority sentiment and capitalize on economic grievances, with the pervasive effects of trade shocks providing fertile ground for such divisive tactics to take root and flourish.

2.3.2 Trade Shock and Racial Resentment

Why does trade shock contribute to the rise of racial bias among whites in the US? The negative effects from trade-induced deindustrialization ripple through not just individual livelihoods, but also the social fabric of local communities. Racial identity is one of the defining characteristics and one of the most important social identities, besides partisanship, of American voters (Hutchings & Valentino, 2004; McDermott & Samson, 2005). Trade shock affected white workers who may seek protection under the white working-class umbrella. When a dominant social group, like the white working class in the U.S., perceives these changes as threats to their longstanding social and economic standing, it can catalyze feelings of resentment and bias, particularly if they view their decline in comparison to the rise or visibility of racial minorities. At the heart of this dynamic lies the social identity theory, which suggests that individuals seek self-esteem, value, and certainty through group affiliation. When white workers feel their esteemed status being eroded due to economic shifts, such as those caused by trade shocks, it's not just about personal economic hardships, but a perceived threat to the entire group's social standing. Coupled with a shifting demographic landscape where whites may no longer hold the majority, there's an innate human tendency to seek certainty and stability. As workers grapple with heightened economic and identity uncertainties, they often turn to in-group identification as a coping mechanism. This can manifest in stronger affiliations with racial or political identities that align with their values.

Concurrently, to make sense of their predicament, these white workers might engage in scapegoating, pinning their misfortunes on out-groups, often racial minorities. This is further exacerbated when certain politicians or KOLs (Key Opinion Leaders), recognizing these sentiments, might stoke divisions with anti-minority narratives, capitalizing on pre-existing cleavages to garner support. The cumulative result is a deepening racial resentment and bias, rooted not just in economic hardships but in the larger battle over identity and social esteem in a rapidly changing world. In the US context, the first and most obvious scapegoat is racial minorities. One most infamous example is the "Muslim Travel Ban" in the early days when Trump took office, it was cheered by most of the Republican base. Another classic example is the anti-Jews movement in the Weimar Republic and the Third Reich after the economic shock from the Great Depression (Bursztyn et al., 2022b, 2022a; Doerr, 2019).

The analysis leads to the following hypothesis:

Hypothesis 1*: White workers in local communities that experience a higher level of trade shock from China will exhibit a higher level of racial resentment.*

2.3.3 Trade Shock and Partisan Affective Polarization

Affective polarization has emerged as a central theme in understanding the deepening partisan divide in contemporary politics. There is a wide consensus and a lot of evidence on the presence of issue polarization among political elites, however, concrete evidence for such polarization at the individual level is lacking (Iyengar et al. 2012, 2019). Shifting the focus from mere policy disagreements, Iyengar and his colleagues delve into the psychological dimensions of partisan polarization. Their research highlights a distinct trend in the U.S.: affective polarization, where individuals' sentiments, feelings, and perceptions about opposing political parties and their affiliates intensify negatively, irrespective of policy stances. This reconceptualization underscores that polarization is not solely about diverging policy views but also deeply entrenched emotional responses and biases against opposing party members.

Why does trade shock-induced deindustrialization affect partisan affective polarization in the US? First and foremost, scholars already found evidence that trade shock leads to partisan issue polarization among both elites and the mass public (Autor et al. 2020a). These policy positions might be on trade policy, affirmative action, redistribution, etc. If this is true, there must be a psychological basis for the issue polarization. Moreover, different racial groups might have different responses to common economic shocks based on their respective special standing in society (Green and McElwee 2019, Baccini and Weymouth 2021). The dominant white group, in their quest for socio-economic stability and identity affirmation, becomes more emotionally aligned with their party and develops deeper resentments towards opposing parties and their affiliates, irrespective of specific policy disagreements. Racial minorities, feeling the heightened resentment and often bearing the blame for exclusionary policies, further consolidate their political affiliations, seeking parties that prioritize their well-being and rights. This reciprocal intensification, rooted in both economic anxieties and identity politics, further exacerbates whites' partisan animosity. Whites' negative feelings towards minorities might be manifested in the form of partisanship, resulting in a deepened emotional divide across party lines in the form of partisan affective polarization among whites. Whites that do not share their values are radical liberals or extreme right-wings, just like there are progressives among the Democrats and RINOs in the GOP.

The analysis leads to the following hypothesis:

Hypothesis 2*: White workers in local communities that experience a higher level of trade shock from China will exhibit a higher level of partisan affective polarization.*

2.3.4 Trade Shock and Public Support for Liberal Policies

Classic trade theory would predict that those adversely affected by the trade shocks may seek governmental interventions to mitigate their economic hardships. This drive is reinforced by the perception that while trade might benefit the nation as a whole, its rewards are unevenly distributed. Consequently, as the economic gap widens due to these shocks, there is an increased public inclination toward policies that promote redistribution, aiming to equitably share the gains and losses from international trade. However, losers from trade are not always compensated, leading to the "failure of compensation" (Frieden 2018). The grievances have different effects on different racial groups (Green and McElwee 2019, Baccini and Weymouth 2021), the dominant white might support less redistribution as the benefits can be ripped off by minorities (A. F. Alesina et al., 2009), while minorities might support more redistribution as the classic trade theory would predict (Baccini and Weymouth 2021).

The analysis leads to the following hypothesis:

Hypothesis 3*: White workers in local communities that experience a higher level of trade shock from China will be less likely to support liberal policies on redistribution.*

2.4 Research Design

2.4.1 Data and Models

I construct three econometric models to test the three hypotheses. The unit of analysis is the Commuting Zone-individual level. A Commuting Zone in the US is an area that consists of several counties that have close economic and social connections. The main predictor, trade shock from China is a 1991-2007 change measure on the commuting zone (Autor et al. 2013, Acemoglue et al. 2016). The main dependent variables are individual attitudes from various surveys after the "shock period": racial resentment is from the Cooperative Election Study (CCES) 2008, 2010, and 2011 studies; partisan affective polarization is from the National Annenberg Election Studies (NAES) 2008 wave dataset; support for liberal policies on redistribution is from the 2016 CCES dataset. I only include white workers, as the theory predicts a white identity backlash across communities in the US. For each model, I match the respondents in surveys to commuting zones where they reside based on county flips. To address the endogeneity concern–as China trade shock might not be exogenous, some domestic factors in the US could explain the labor market reshuffling, I follow Autor et al. (2013) and Acemoglu et al. (2016) and adopt a shift-share instrumental variable strategy. The main instrumental variable is a shift-share change of Chinese exports to eight other "similar" (Ballard Rosa et al. 2021) advanced economies in Western Europe in the same period. They argue that the sudden rise of Chinese exports to the US is mainly due to domestic reforms in China and not necessarily due to US labor market characteristics.

2.4.2 Dependent Variables

Racial Resentment

The racial resentment metric I plan to employ is based on the framework provided by Kinder & Sears (1981) and further developed in the analysis by (Acharya et al., 2016), using data from the Cooperative Congressional Election Study (CCES). Following the methodology of Acharya et al. (2016), the CCES survey data from 2008, 2010, and 2011 will be aggregated, yielding a total of 93,321 observations across 703 US commuting zones. The 2010 CCES survey includes two pivotal questions that measure racial attitudes. In the surveys, participants rate their agreement with a statement using a scale from one to five, with one indicating strong disagreement and five indicating strong agreement. The questions are: “The Irish, Italian, Jews and various other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors.” In addition, respondents are asked to rate their agreement with the statement: “Generations of slavery and discrimination have created conditions that make it difficult for Blacks to work their way out of the lower class.” (CCES 2008, 2010). The 2011 CCES includes a repetition of the first statement from the 2010 survey. To create a consistent measure across surveys, responses are normalized to a 0 to 1 scale, where higher values indicate greater levels of racial resentment.

This operationalization of racial resentment serves as a crucial variable in examining the attitudinal impacts of historical and socio-political factors on contemporary racial dynamics. The conceptualization of racial resentment, particularly towards African Americans, is deeply rooted in the distinct historical and social fabric of the United States, which has been characterized by unique and persistent forms of discrimination and inequality (Kinder and Sears, 1981). This singular history of slavery, segregation, and ongoing systemic barriers necessitates a focused approach to measuring racial attitudes, one that captures the nuanced forms of prejudice that African Americans face (Bobo & Kluegel, 1993). The use of specific questions from the Cooperative Congressional Election Study (CCES) surveys, as outlined by Kinder and Sears, is designed to reflect the complex interplay between perceptions of traditional American values like individualism and the acknowledgment of systemic hindrances to African American advancement (Hutchings & Valentino, 2004). By concentrating on African Americans, researchers can isolate and analyze attitudes that are deeply embedded in the nation's socio-political discourse and that are often amplified in debates surrounding policies aimed at redressing historical injustices (Sniderman & Piazza, 1993). This measurement strategy is also validated by the symbolic racism theory, which posits that modern forms of racial prejudice manifest through beliefs that minorities, particularly African Americans, contravene fundamental American principles (Sears & Henry, 2003).

However, it also should be noted that the racial resentment scale, although widely used in the literature, has its limitations. Some scholars argue that it measures the conservative ideology instead of racial bias (Cramer, 2019; Sniderman & Carmines, 1997; Sniderman & Tetlock, 1986), as the questions are framed around principles of individualism, which could skew the measurement towards capturing ideological beliefs rather than explicit racial attitudes. . Other critics argue that it only measures the explicit racism rather than the implicit racial bias. Additionally, the scale's primary focus on white/Black dynamics does not fully capture the racial and ethnic diversity of contemporary America. As the country becomes increasingly diverse, it's crucial to expand our analytical frameworks to include a wider range of racial groups. We should "move beyond the white/Black dichotomy" to better understand the complex landscape of racial attitudes (K. Cramer, 2019; Stephens-Dougan, 2021). This is especially pertinent as racial bias increasingly intertwines with views on immigration, highlighted by contentious policies and rhetoric such as the Muslim Travel Ban, the "Build the Wall" campaign regarding the US-Mexico border, and the rise in anti-Asian sentiment. Finally, the original measurement, grounded in the psychological tradition of (Allport, 1954), could benefit from incorporating more contemporary theories that emphasize the role of perceived group social status threats (Blumer, 1958; Bobo & Hutchings, 1996). These perspectives argue that racial attitudes are not just products of individual prejudices but are also deeply influenced by perceived threats to in-group status and resources. This broader approach could provide a more nuanced understanding of the mechanisms driving racial bias and resentment, including how they relate to broader socio-political contexts and policies.

Affective Polarization

Following Lelkes et al., 2017), affective polarization is measured through feeling thermometer surveys. The main data source is from the National Annenberg Election Studies (NAES) 2008 survey. I only include non-Hispanic whites, the main reason for only including whites is that the theory is a white identity theory. Following current studies in the literature (e.g Ballard Rosa et al. 2021a, Broz, Frieden, and Weymouth 2022, Baccani and Weymouth 2021), it predicts that partisan affective polarization might work as a mechanism by which trade shock affects the rise of right-wing populism among whites in the US. The main purpose is to test whether partisan affect or racial affect is more prevalent among whites. The final dataset has 45,600 observations across 690 commuting zones in the US. Within the National Annenberg Election Studies (NAES) 2008 wave dataset, respondents indicate their sentiments towards both their affiliated party or candidates and opposing parties or candidates using a 10-point scale. A higher score denotes more positive feelings. Affective polarization is quantified by determining the difference between in-party and out-party thermometer readings. This method stands as the predominant approach to measuring affective polarization in contemporary research. I rescale it to range between 0 and 1, a higher value means higher levels of affective polarization.

Support for Liberal Policies

This data comes from the 2016 CCES dataset. In this dataset, people were asked their views on various policy areas like minimum wages, government spending on welfare, healthcare, and education. If someone supports a policy, it's marked as "1", and if they don't, it's "0". The full dataset has entries from 62,590 individuals across 2,236 counties. However, since my main interest is in understanding the perspectives of white individuals, I'm focusing on a subset that has 43,320 entries from 2,175 counties.

2.4.3 Independent Variables

The independent variable measures the twenty-year changes in trade exposure of individuals in a Commuting Zone in the US from 1991 to 2007 comes from Autor et al. (2013). This measure is different from previous measures in the sense that it takes into account the regional unemployment factors. The original data on trade used in the study comes from the United Nations Comtrade Database concerning U.S. imports, detailed at the six-digit level of the Harmonized System. To calculate the impact of trade on employment, the authors used a formula that considers the initial employment in a specific region (a commuting zone in the US) and the change in U.S. imports from China in a certain industry over a set period (from 1991 to 2007). This calculation is intended to reflect the structural change of local industry employment over a relatively long period of time. The measure is on the Commuting Zone (CZ) level, which is a subset of the state and consists of several counties. This variable has a minimum value of 0.1 and a maximum value of 6.

2.4.4 Instrumental Variables

One concern with the above conception of trade shock from China and affective polarization in the US is that China's exports in the US may be related to industrial "import demand shocks" (Autor et al. 2013, 2020) in the US. Because both affective polarization and imports in the US may be positively related to some unobserved demand increases in the US, the OLS model will underestimate the real impact. In this case, an instrumental variable approach is more appropriate as it can deal with the potential endogeneity issue discussed above.

Because the trade exposure to Chinese import competition in the US can be correlated with some unknown factors, instrumental variables can help to cut the relations between the endogenous variable and the error term. Following the previous design on the China trade shock, this paper also adopts an instrumental variable approach. An instrumental variable is often correlated with the explanatory variable but not with the dependent variable. During the period in which China's exports to the US changed rapidly, China experienced dramatic economic growth due to the "Reform and Opening Policy". The increase in China's trade exposure in the US is related to domestic factors like lowering trade barriers, accession to WTO, reforming the centralized economic system, etc. However, these factors have no direct relation with US partisanship attitudes. China's trade volume increases with other advanced economies are due to these country-specific factors, thus it can help to capture these changes and serve as an exogenous instrument.

The instrument in this paper is also from Autor et al. (2013), it measures the trade growth and composition of Chinese exports to eight other advanced economies (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). It can capture the supply-driven component of trade shock from China in the US. The construction of this instrumental variable is based on the China trade shock method described above. This measure aims to isolate the portion of the trade impact that results from China’s export activities on the U.S. market. This change is assessed to understand how China's export growth may have indirectly affected U.S. industries through competitive pressures. It is different from the China trade shock equation constructed above in that it replaces US imports from China in the designated time period (1993 to 2007) with China’s exports to other eight advanced market economies during the time period concerned. Thus, it also varies on the commuting zone (CZ) level as the China shock measure does.

2.4.5 Controls

For each model, I include some regional-level as well as individual-level characteristics as controls. On the regional level, following common practice in the literature, I adopt some indicators from the ICPSR County Characteristics (2000 - 2007) as controls. These controls include median ages, percent black, percent white, census region, level of education, median income, population density, and the male-to-female ratio, etc. To control for long-term cultural backgrounds on the racial resentment model, following Acharya et al. (2016), I also include the percentage of slaves in each county in 1860. I also include some individual-level characteristics such as age, education level, gender, partisanship, etc. Table 1 shows the definitions of variables in these models.

Table 2-1. Variable definitions

Variable	Definitions
Trade Shock	A 20-year change measurement on US CZs' exposure to Chinese imports 1991-2007;
Black Population	Black population number on the county level, logged;
Slave 1860	Percentage of slaves on the county level in 1860;
White/Black Income Ratio	The ratio between white and black people's average income level;
Edu Cut	A 6-category cut for individual education levels;
Religion	Whether respondent is a church goer;
Income Cut	A 5-category cut on individual income levels;
Female	A dummy variable on the sex of respondent;
Age	Age of respondent in the year examined;
Republican/Party ID	Party affiliation;
Unemployment	County level unemployment rate;
Internet Providers	Number of internet providers on the county level, logged;
Income	Individual level income, continuous variable;
Region	A 5-Category variable on regions in the US;
Black percentage	Percentage of black population on the county level ;
White percentage	Percentage of white population on the county level;
Male percentage	Percentage of male on the county level;
Low edu county	Counties with lower-than-average education rate;
Population density	Population density on the county level;
Anti-immigration	A 5-category variable on individual's anti-immigration levels;
Family Econ Worse	A dummy variable on whether one feels his/her family experience worse economic situations;
Family income	Family income level in the past four years;
Unemployed	A dummy variable on whether the person is unemployed;
Foreign born change 00-14	The rate change of foreign-born population on the county level;
Union member	A dummy variable on whether one is a union member;
College	A dummy variable on whether one has a college degree;
Racial attitudes	A 5-category variable on the level of one individual's conservative racial attitudes;

2.5 Results

2.5.1 Results on Racial Resentment

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 2-1. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
Trade Shock	704	0	3.5	2.5	0.0	3.1	49.0
Automation Shock	704	0	0.3	0.7	−3.7	0.3	6.1
Racial Resentment	10	46	3.8	1.2	1.0	4.0	5.0
Black Proportion	14495	11	0.1	0.1	0.0	0.0	1.0
Slave Percentage 1860	1176	7	0.1	0.2	0.0	0.0	0.9
White/Black Income Ratio	2524	1	1.5	0.4	0.2	1.5	10.5
Unemployment	2832	0	0.1	0.0	0.0	0.1	0.2
Female	2	0	0.5	0.5	0.0	1.0	1.0
Age	79	0	52.1	15.4	18.0	54.0	96.0
Republican	2	0	0.5	0.5	0.0	0.0	1.0

Figure 2-2. Categorical variables

		N	%
Republican	0	49740	53.3
	1	43581	46.7
Female	0	45531	48.8
	1	47790	51.2
Income cut	<20k	9069	9.7
	100-150k	11401	12.2
	150k+	8931	9.6
	20-50k	27259	29.2
	50-100k	30472	32.7

I fit an instrumental variable model (table 2-3) with commuting zone fixed effects of trade shock and racial resentment. The results show that trade shock has a positive but non-significant coefficient on racial resentment. The coefficient is very small, 0.004, indicating that one unit increase will only lead to a 0.004-point increase in racial resentment. It means that the evidence does not support the impact of trade shock on racial resentment. However, this result does not mean that labor market reshuffling does not have any impact on racial tensions, as trade shock is only one source of the manufacturing job decline.

Table 2-2. OLS model

Trade and Racial Resentment

	Dependent variable:
	Racial Resentment
Trade Shock	0.001
	(0.002)
Black Percentage	-0.128***
	(0.048)
Slave Percentage 1860	0.378***
	(0.036)
White/Black Income Ratio	-0.010
	(0.012)
High School	0.021
	(0.038)
Some College	-0.279***
	(0.038)
2-year College	-0.177***
	(0.041)
4-Year College	-0.560***
	(0.038)
Postgrad	-0.838***
	(0.040)
Religion	0.258***
	(0.012)
Income(100-150k)	-0.118***
	(0.023)
Income(150k+)	-0.059**
	(0.025)
Income(20-50k)	-0.023
	(0.019)
Income(50-100k)	-0.078***
	(0.019)
Female	-0.038***
	(0.011)
Age	-0.002***
	(0.0004)
Republican	0.971***
	(0.011)
Intercept	3.694***
	(0.048)
CZ Fixed effects?	Yes
Observations	37,531
Adjusted R^2	0.266
Residual Std. Error	1.032 (df = 37513)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2-3. Instrumental variable model

Trade and Racial Resentment

	Dependent variable:
	Racial Resentment
Trade Shock	0.004
	(0.050)
Black Percentage	-0.230***
	(0.051)
Slave Percentage 1860	0.267***
	(0.097)
White/Black Income Ratio	-0.042***
	(0.015)
High School	0.021
	(0.038)
Some College	-0.262***
	(0.038)
2-year College	-0.168***
	(0.041)
4-Year College	-0.537***
	(0.038)
Postgrad	-0.816***
	(0.040)
Religion	0.237***
	(0.012)
Income(100-150k)	-0.092***
	(0.023)
Income(150k+)	-0.035
	(0.025)
Income(20-50k)	-0.016
	(0.019)
Income(50-100k)	-0.061***
	(0.020)
Female	-0.041***
	(0.011)
Age	-0.002***
	(0.0004)
Republican	0.959***
	(0.012)
Intercept	3.928***
	(1.027)
CZ Fixed effects?	Yes
Observations	37,531
Adjusted R^2	0.276
Residual Std. Error	1.026 (df = 37010)
Note:	*p<0.1; **p<0.05; ***p<0.01

2.5.2 Results on Affective Polarization

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 2-3. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
Trade Shock	690	0	3.6	2.7	0.0	3.1	49.0
Automation Shock	690	0	0.4	0.7	−3.7	0.3	6.1
Affective Polarization	865	14	0.3	0.3	−1.0	0.2	1.0
Black Percentage	2762	0	0.1	0.1	0.0	0.1	0.9
White Percentage	2769	0	0.8	0.1	0.1	0.9	1.0
Male Rate	2765	0	0.5	0.0	0.4	0.5	0.7
Internet Providers	961	0	10.7	3.3	2.7	10.5	20.7
Unemployment	105	1	5.0	1.3	1.9	4.9	16.0

Figure 2-4. Categorical variables

		N	%
Party ID	Democrat	20019	43.9
	Republican	20677	45.3
Female	Female	26107	57.3
	Male	19493	42.7
Age cut	Age: 1st Quartile	10226	22.4
	Age: 2nd Quartile	10858	23.8
	Age: 3rd Quartile	12715	27.9
	Age: 4th Quartile	11403	25.0
	Age: Missing	398	0.9
Income cut	Income: 1st Quartile	9728	21.3
	Income: 2nd Quartile	13926	30.5
	Income: 3rd Quartile	6280	13.8
	Income: 4th Quartile	10122	22.2
	Income: Missing	5544	12.2
Region	1: Northeast	9004	19.7
	2: Midwest	12492	27.4
	3: South	15220	33.4
	4: West	8770	19.2

I fit an OLS as well as an instrumental variable model on trade shock and affective polarization with commuting zone fixed effects. The IV model (table 2-5) results show that trade shock has a small positive coefficient of 0.001, which is also very small. One unit change in trade shock will only lead to a 0.001-point change in affective polarization. Trade shock is not statistically significant. The non-significant results mean that affective polarization is not the main mechanism that trade shock leads to backlash against globalization.

Table 2-4. OLS model on trade shock and affective polarization

Trade Shock and Affective Polarization	
	Dependent variable:
	Affective Polarization
Trade Shock	-0.003
	(0.006)
Unemployment	-0.004***
	(0.002)
Internet Providers	-0.001
	(0.007)
Republican	0.107***
	(0.002)
Female	-0.006***
	(0.002)
Age 4th Quartile	0.021***
	(0.003)
Some College	-0.008***
	(0.002)
Income 4th Quartile	0.008***
	(0.003)
Midwest	0.044**
	(0.022)
South	0.027
	(0.023)
West	0.054
	(0.049)
Black Percentage	0.049
	(0.034)
White Percentage	0.034
	(0.031)
Male Percentage	-0.097
	(0.102)
Low Education County	-0.002
	(0.005)
Population Density	0.034**
	(0.016)
Intercept	0.510***
	(0.095)
CZ Fixed effects?	Yes
Observations	39,108
Adjusted R^2	0.107
Residual Std. Error	0.165 (df = 38400)
Note:	*p<0.1; **p<0.05; ***p<0.01

Note: This is an OLS model, Certain variables have been omitted for brevity.

Table 2-5. Instrumental variable model on trade shock and affective polarization

Trade Shock and Affective Polarization

	Dependent variable:
	Affective Polarization
Trade Shock	0.001
	(0.007)
Unemployment	-0.004***
	(0.002)
Internet Providers	-0.001
	(0.007)
Republican	0.107***
	(0.002)
Female	-0.006***
	(0.002)
Age 4th Quartile	0.021***
	(0.003)
Some College	-0.008***
	(0.002)
Income 4th Quartile	0.008***
	(0.003)
Midwest	0.044**
	(0.022)
South	0.027
	(0.023)
West	0.054
	(0.049)
Black Percentage	0.050
	(0.034)
White Percentage	0.034
	(0.031)
Male Percentage	-0.095
	(0.102)
Low Education County	-0.003
	(0.005)
Population Density	0.034**
	(0.016)
Intercept	0.505***
	(0.095)
CZ Fixed effects?	Yes
Observations	39,108
Adjusted R^2	0.107
Residual Std. Error	0.165 (df = 38400)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Note: This is an Instrumental Variable model, Certain variables have been omitted for brevity.

2.5.3 Results on Public Support for Liberal Policies

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 2-5. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
Minimum Wage	3	0	0.7	0.5	0.0	1.0	1.0
Welfare	3	44	0.3	0.5	0.0	0.0	1.0
Healthcare	3	41	0.8	0.4	0.0	1.0	1.0
Education	3	38	0.9	0.4	0.0	1.0	1.0
Trade Shock	668	0	3.5	2.5	0.0	3.1	49.0
Automation Shock	668	0	0.3	0.7	−3.7	0.3	6.1
Conservative Racial Attitudes	22	13	0.3	0.2	0.0	0.3	1.0
Age	79	0	50.0	16.9	18.0	52.0	98.0
Unemployment	2557	0	74.2	48.2	−87.7	73.5	358.6
Foreign born change	2505	0	56.3	56.6	−100.0	42.5	1100.0
Female	2	0	0.5	0.5	0.0	1.0	1.0
Latino Percentage Change 00-14	2518	0	97.9	69.8	−100.0	84.2	1684.0
Family Econ Worse	6	0	0.5	0.3	0.0	0.5	1.0
Relative Deprivation	3	10	0.6	0.5	0.0	1.0	1.0
Manufacturing job change 00-14	2557	0	−26.0	12.6	−90.1	−27.2	216.0
Anti-immigration	5	0	0.5	0.4	0.0	0.5	1.0
Union Member	4	0	1.5	0.7	1.0	1.0	3.0
Conservative Ideology	5	0	3.1	1.1	1.0	3.0	5.0
College	2	0	0.4	0.5	0.0	0.0	1.0
South	2	0	0.3	0.5	0.0	0.0	1.0
Family Income	13	10	6.4	3.2	1.0	6.0	12.0
Unemployed	2	0	0.0	0.2	0.0	0.0	1.0

Figure 2-6. Categorical variables

Party ID	N	%
Democrat	14142	31.8
Independent	17425	39.1
Republican	12929	29.0
NA	13	0.0

Table 2-7 shows the IV model results on trade shock and public support for liberal policies. Trade shock has a negative and significant coefficient in the welfare model. The effect is also relatively small, with one unit change in trade shock that can only lead to a 0.3 percent change in the probability of supporting government spending on welfare. Trade shock has positive but non-significant coefficients on all other three models on minimum wage, healthcare, and education. The coefficients are also very small in all three models. The coefficient on minimum wage is extremely small, 0.00004. The results show that there is limited evidence that trade shock could directly affect public support for redistribution.

Table 2-6. OLS models on trade and public support for liberal policies

Trade Shock and Support for Liberal Policies

	Dependent variable:			
	Minimum Wage	Welfare	Healthcare	Education
	(1)	(2)	(3)	(4)
Trade Shock	-0.001	-0.001	0.0002	0.0004
	(0.001)	(0.001)	(0.001)	(0.001)
Racial Attitudes	-0.407***	-0.415***	-0.476***	-0.403***
	(0.012)	(0.013)	(0.013)	(0.011)
Anti-immigration	-0.141***	-0.206***	-0.097***	-0.074***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Econ Worse	-0.083***	-0.060***	-0.079***	-0.088***
	(0.009)	(0.011)	(0.010)	(0.009)
Unemployment	-0.00001	-0.0001**	-0.0002***	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Family Income	-0.016***	-0.026***	-0.019***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	0.066***	0.103***	0.023*	-0.006
	(0.011)	(0.013)	(0.012)	(0.010)
Foreign-born Change (00-14)	0.00002	0.00005	0.00003	0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Union Member	0.014***	0.003	0.005	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.027***	-0.064***	0.033***	0.050***
	(0.004)	(0.005)	(0.005)	(0.004)
Conservative Ideology	-0.086***	-0.096***	-0.070***	-0.040***
	(0.003)	(0.003)	(0.003)	(0.003)
South	0.008	0.074***	-0.016	0.002
	(0.023)	(0.026)	(0.024)	(0.022)
College	-0.081***	0.031***	-0.069***	-0.049***
	(0.005)	(0.006)	(0.005)	(0.004)
Age	0.001***	-0.001***	0.001***	-0.001***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Independent	-0.109***	-0.172***	-0.080***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.005)
Republican	-0.172***	-0.190***	-0.121***	0.006
	(0.007)	(0.008)	(0.007)	(0.006)
Intercept	1.268***	1.329***	1.422***	1.334***
	(0.036)	(0.040)	(0.037)	(0.033)
CZ Fixed effects?	Yes	Yes	Yes	Yes
Observations	34,550	22,247	23,357	24,616
Adjusted R^2	0.304	0.437	0.328	0.218
Residual Std. Error	0.398 (df = 34483)	0.359 (df = 22180)	0.343 (df = 23290)	0.304 (df = 24549)
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This is an OLS model, Certain variables have been omitted for brevity.

Table 2-7. IV models on trade and public support for liberal policies

Trade Shock and Support for Liberal Policies

	Dependent variable:			
	Minimum Wage	Welfare	Healthcare	Education
	(1)	(2)	(3)	(4)
Trade Shock	0.00003	-0.003*	0.002	0.001
	(0.001)	(0.002)	(0.001)	(0.001)
Racial Attitudes	-0.409***	-0.414***	-0.476***	-0.403***
	(0.012)	(0.013)	(0.013)	(0.011)
Anti-immigration	-0.137***	-0.207***	-0.096***	-0.074***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Econ Worse	-0.079***	-0.060***	-0.079***	-0.088***
	(0.009)	(0.011)	(0.010)	(0.009)
Unemployment	-0.0001*	-0.0001**	-0.0002***	-0.0001*
	(0.00005)	(0.0001)	(0.0001)	(0.0001)
Family Income	-0.012***	-0.026***	-0.019***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	0.070***	0.103***	0.023*	-0.006
	(0.011)	(0.013)	(0.012)	(0.010)
Foreign-born Change (00-14)	-0.00004	0.00004	0.00004	0.00002
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Union Member	0.017***	0.003	0.005	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.026***	-0.064***	0.033***	0.050***
	(0.005)	(0.005)	(0.005)	(0.004)
Conservative Ideology	-0.087***	-0.096***	-0.070***	-0.040***
	(0.003)	(0.003)	(0.003)	(0.003)
South	0.003	0.073***	-0.016	0.002
	(0.005)	(0.026)	(0.024)	(0.022)
College	-0.080***	0.031***	-0.068***	-0.049***
	(0.005)	(0.006)	(0.005)	(0.004)
Age	0.001***	-0.001***	0.001***	-0.001***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Independent	-0.111***	-0.172***	-0.080***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.005)
Republican	-0.176***	-0.190***	-0.121***	0.006
	(0.007)	(0.008)	(0.007)	(0.006)
Intercept	1.240***	1.337***	1.414***	1.331***
	(0.018)	(0.040)	(0.038)	(0.033)
CZ Fixed effects?	Yes	Yes	Yes	Yes
Observations	34,550	22,247	23,357	24,616
Adjusted R^2	0.299	0.437	0.328	0.218
Residual Std. Error	0.399 (df = 34530)	0.359 (df = 22180)	0.343 (df = 23290)	0.304 (df = 24549)
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This is an Instrumental Variable model, Certain variables have been omitted for brevity.

2.6 Conclusion

In this chapter, I establish a theoretical framework linking trade shocks to white identity politics, characterized by racial divisions and partisan affective polarization. Additionally, I explore the potential of redistributive policies to mediate the influence of trade shocks on the rise of right-wing populism. I rigorously test two hypothesized mechanisms—social identity and the policy-driven need for compensation—to determine their roles in catalyzing right-wing populist sentiments as a consequence of trade shocks. Contrary to prevailing assertions in the literature, the findings indicate that neither identity politics nor policy needs function as mediators in an anticipated manner. The insufficiency of trade shock as a sole catalyst suggests that its ability to incite identity politics or calls for redistribution may be overstated.

The lack of micro-level support for the supposed linkage between trade shocks and right-wing populism suggests that the association observed at the macro level may not reflect a causal relationship but rather a correlation influenced by other factors. The literature on trade shock has issues on two fronts: its indirect impact on negative political outcomes through labor market effects, devoid of a direct link to political attitudes (Bisbee and Rosendorff, 2019, 2020), and the misalignment between the dependent variables studied and the actual influence of trade, with trade issues holding low political salience regardless of explicit trade cues (Bisbee and Rosendorff, 2019; Rho and Tomz, 2015; Guisinger, 2017). These insights question the causal narratives that attribute political phenomena solely to trade shocks.

Therefore, the policy implications derived from these insights suggest that strategies to mitigate political backlash should not focus exclusively on trade policies. A more comprehensive approach, potentially incorporating labor market reforms and broader economic adjustments, may be necessary to address the underlying causes of discontent that are attributed to, but not exclusively caused by, trade shocks. This broader perspective is essential for crafting effective policies that can alleviate the political and social repercussions associated with economic disruptions.

CHAPTER 3: AUTOMATION, IDENTITY POLITICS, AND PUBLIC SUPPORT FOR LIBERAL POLICIES

3.1 Introduction

3.1.1 History of Automation

Technological change is one of the main drivers of labor market reshuffling, perhaps even more so than trade (Goos et al., 2014; Tella & Rodrik, 2020). The history of automation and its impact on labor and society is one characterized by technological progress and human adaptation. The Luddite movement of the early 19th century represents a seminal moment in the history of labor's resistance to automation, as skilled textile workers in England protested the mechanization brought about by the Industrial Revolution, fearing job losses and a decline in craftsmanship. This set the stage for successive waves of technological advancement that have continuously reshaped industry: the adoption of Henry Ford’s assembly line in the early 20th century revolutionized manufacturing, the post-World War II era saw the integration of computers in industrial processes, and the digital revolution brought forth a significant leap in automation with robotics and artificial intelligence. The COVID-19 pandemic accelerated the adoption of automation as businesses sought to reduce human contact, maintain operations with a reduced workforce, and increase efficiency in the face of supply chain disruptions. These technological shifts sparked debates over the trade-offs between increased productivity and potential job displacement, a conversation that persists today as advanced AI and robotics challenge both blue-collar and white-collar professions, emphasizing the need for societal adaptation and skill development to navigate the dual forces of innovation and disruption.

3.1.2 Automation and Deindustrialization in the US

Computer-based technologies, such as personal computers and algorithms introduced since the 1970s, have typically benefited workers with higher education and displaced those performing routine tasks. This phenomenon has contributed to a shrinking middle class and widening income gaps, with job polarization being a major driving force (Acemoglu et al. 2022). Evidence shows that that manufacturing workers have a higher chance (52%) of being affected by job automation through advanced technologies than workers in other sectors (28%) (Acemoglu et al. 2022). Robots and AI are especially prevalent in manufacturing, which increases the likelihood of automation in this sector. Interestingly, the use of specialized, non-robotic equipment poses a similar automation risk to manufacturing workers as robots do. Advanced technologies like specialized software and cloud computing also contribute to a higher risk of automation in manufacturing jobs.

Automation continues to expand in U.S. manufacturing today, with companies increasingly investing in robots and other automated systems to boost productivity and counter global competition. The Robotic Industries Association (RIA) reported that in 2021, robot sales in the U.S. had surged, with industries ordering over 29,000 units, a 28% increase from 2020. Beyond manufacturing, automation is growing in the service sector, including food service, hospitality, and retail, particularly after the pandemic pushed businesses to find contactless solutions. Artificial intelligence is becoming more integrated with automation, leading to more sophisticated and autonomous systems capable of decision-making processes and adapting to new environments. The recent Writers Guild of America strike in Hollywood exemplifies the expanding threat of automation, even in traditionally creative domains.

3.1.3 The Gap in the Literature

As the rise of automation reshapes job markets, its distributional effects and potentially disruptive nature have captured the attention of political scientists, particularly in the context of its impact on right-wing populism. Drawing parallels to the body of research on trade shocks, recent studies have provided robust regional evidence linking automation shocks to increased support for right-wing populist parties and politicians. However, the underlying mechanisms of this correlation remain somewhat ambiguous and are not thoroughly examined and tested (González-Rostani, 2022). Two theoretical frameworks have been proposed to explain this phenomenon. The first is the classical political economy model, which focuses on economic loss and the demand for redistribution as driving factors. The second is the misattribution-social identity model (Gallego & Kurer, 2022), which suggests that individuals may incorrectly attribute economic hardships to political and social outgroups, reinforcing in-group identities. Yet, the social identity elements of this model require further exploration and empirical testing at the individual level. Additionally, there is no consensus on whether the labor market disruptions caused by automation prompt the implementation of policies aimed at mitigating such effects. The evidence is inconclusive, with different studies yielding varied findings on the presence and effectiveness of policy responses to automation-induced labor market changes.

3.1.4 Plan of this Chapter

This study directly examines whether and how automation shock could affect identity politics and public support for redistribution policies in the US. Similar to the trade shock literature, if automation contributes to the rise of radical right-wing populism mainly through its effect on the labor market and the ensuing social identity backlashes, it will have a direct impact on the negative identity politics that are characterizing US politics nowadays. Specifically, automation shock would contribute to the rise of racial tensions and partisan affective polarization among the socially dominant group, the whites, in the US. Identity politics, especially racial identity plays a vital role in white people's support for redistribution, I would expect that automation-affected white workers would be less likely to support redistribution, contrary to some existing literature. Despite findings linking automation shock to populist voting in developed economies, automation isn't a prominent political issue. Unlike trade and immigration, where voters back protectionism and politicians rally against foreign influence, the political impact of automation is primarily through its effects on the labor market and subsequent political behaviors. Therefore, I expect that automation would work through identity politics like partisan affective polarization and racial division to affect the rise of right-wing populism.

Using nationally representative survey data, the empirical tests in this chapter examine how regional variation in the adoption of robots affects negative identity politics in the US. It also examines how local automation shock affects public support for redistribution. The study also mainly focuses on whites, as it is the socially dominant group in the US. The results show that however, automation does not have any significant effect on either partisan affective polarization or racial resentment. It also has a limited effect on public support for redistribution, contrary to some works.

This chapter contributes to at least two literatures: the automation shock literature and the negative politics literature. Within the automation literature, this study probes the mechanisms potentially linking automation shock to right-wing populism in the US. The identity politics literature examines whether economic shocks, such as automation, directly and independently influence negative partisan affective polarization and racial divisions.

The structure of this chapter is as follows: The subsequent section reviews the literature on automation shock and its influence on the rise of right-wing populism. I then present theories explaining how automation shock might directly impact negative white identity politics, suggesting that these politics may serve as mechanisms through which automation shock fosters right-wing populism. The fourth section details the research design, followed by an empirical section showcasing the results. I conclude by discussing why automation does not significantly affect identity politics or public support for redistribution in the US.

3.2 The Literature

3.2.1 Automation Shock and Labor Market Displacement

Technological developments are vital to economic development and the improvement of living standards, however, due to their displacement effects, it also has distributional effects on the labor markets. This is what (Keynes, 1931) called "technological unemployment". Goldin & Katz (1998) examine the development of technology in the 19th and 20th centuries, they find that in the early 20th century, the electrification of factories replaced many unskilled workers and raised the high demand for high-skilled workers. With the computerization process beginning decades ago, this effect has become more prominent (Nordhaus, 2007). The job market is becoming more polarized than ever with the increase of people on the high-wage high-skill side and the low-skill low-wage service jobs but a shrink in the middle (Anelli et al., 2023; D. H. Autor & Dorn, 2013).

In a series of seminal papers, (Acemoglu & Restrepo, 2018, 2020, 2022) examine the effects of automation on local labor markets on the commuting zone level in the US in the 1990s and 2000s. By adopting the data and definitions of industrial robots from the International Federation of Robotics (IFR), Acemoglu & Restrepo (2018, 2020, 2022) constructed an index to measure the extent to which a local area--a commuting zone--is exposed to industrial robots. This measurement is based on 19 industries in the US from 1993 to 2007, as 1993 is the first year the data is available.

In the long run, the automation process will have an equilibrium because it displaces many low-skill jobs, but it also creates a lot of new jobs. New tasks are emerging, this trend further exacerbates the bias against low-skill workers. By taking into consideration previous employment and wages from the examined periods, they find that one new robot per thousand workers will reduce 0.2 percent employment/population ratio and 0.42% wages. By using a similar strategy, (Chiacchio et al., 2018) found similar trends in six European countries. They also find that automation has adverse effects on local employment, the only difference is that they do not find adverse effects on wages. (Dauth, 2018) perform similar research in Germany, their findings are contrary to that of Chiacchio et al. (2018). By using matched employer-employee data, they find that when displaced workers switch to higher-skill jobs, the overall unemployment does change too much while the wage inequality is increasing. (Frey & Osborne, 2017) estimate the potential job displacement of automation in the future. They predict that in the coming two decades, 47% of US workers will be in high-risk occupations of losing jobs to automation. These high-risk occupations mainly hire low-wage and less-educated workers.

3.2.2 Automation and Negative Politics

Works on the political consequences of automation find consistent evidence of automation and the rise of right-wing populism in developed democracies. In the US, Frey et al. (2018) examine the effect of automation on US presidential elections and find that manufacturing workers are more likely to support Donald Trump when they are more affected by automation. Gallego et al. (2018) study computerization in UK politics. They find that workers more influenced by IT revolutions in their sectors will be more likely to vote for Conservatives and UKIP—the radical-right party in the UK. (Bó et al., 2018) studied the political consequences of automation in Sweden, and they found similar evidence that automation will lead to higher levels of support for radical right parties. In one working paper, Anelli et al. (2023) study the politics of automation on a cross-country level. They focus on 17 Western European states. By using the measurement strategy of automation exposure on a regional level Acemoglu and Restrepo (2018), examine the effects of automation shock on nationalism and radical-right populism and find strong evidence that automation does lead to higher levels of support for these unconventional politics. Most of these works mainly focus on radical-right parties or prominent black swan phenomena like the election of Donald Trump in the US. But similar to an economic shock from trade, these are just the results or things with “outcome significance” (Margalit 2019). To fully understand the political consequences of automation and the causal mechanisms, we need to take other important political aspects into the examination. One vital aspect is affective polarization which has become prominent in US politics in recent decades, even before the election of Donald Trump.

3.2.3 Mixed Findings on Automation and Public Support for Redistribution

Conventional political economy theories suggest that exposure to labor market uncertainties or actual economic downturns impacts people's economic concerns, which in turn influences their political choices (Gallego & Kurer, 2022). In the context of digitalization, the potential threat of job loss due to automation might naturally drive workers to demand more economic safeguards, such as redistribution. However, the studies on automation and political preferences reveal a more nuanced relationship. Thewissen & Rueda (2017) and Kurer & Häusermann (2022) both suggest that there is a correlation between automation risk and demand for certain welfare policies, like unemployment benefits, but not necessarily broader redistribution measures. This could imply that workers fear temporary unemployment due to automation but believe they can eventually adapt or transition, thus not demanding wider systemic changes. Further complicating the picture, other studies like Gallego and Kurer (2022) and Zhang (2022) either find no connection between automation risk and redistribution preferences or establish that only certain rhetoric can elicit such demands.

3.3 Automation Shock and White Identity Politics

Two models are used by scholars to explain why automation shock led to the rise of right-wing populism: policy response and social identity response (see Galego and Kurer 2022 for a review). However, apart from the empirical findings that link automation shock to support for populism in developed economies, automation is generally not a high-profile political issue in most countries. At the individual level, voters typically don't favor restrictions on the adoption of new technology. On the meso-level, political entrepreneurs and parties lack a platform to mobilize around automation. This contrasts with trade and immigration, where voters can rally behind protectionism and taxes, and politicians and parties can capitalize on anti-foreign sentiments (Chaudoin & Mangini, 2023, Gallego and Kurer 2022). While the backlash against globalization may stem from those adversely affected by trade, necessitating compensatory mechanisms, automation's influence seems to be limited to its direct impact on the labor market and therefore its indirect effects on political behaviors.

In most of the trade shock and populism literature, trade cues are not specifically taken into account, i.e., policy responses are not the main channel that trade shock leads to populism politics. Similar to automation shock, trade shock affects politics mainly through its effect on the local labor market. Thus, I expect that the four main mechanisms that help to explain the link between trade and white identity politics also apply to automation shock. This expectation is built on the assumption that white workers cannot distinguish the different sources of labor market reshuffling in their local communities. Evidence to support this assumption is discussed in detail in the third chapter. The negative identity politics can be manifested in two most prominent forms: Racial identity division and partisan identity division. It is based more on the psychological aspect rather than the policy/issue aspect.

3.3.1 Automation and Racial Division

Why could automation-induced labor market reshuffling affect the racial attitudes of white workers? When white workers in the US, who have traditionally been a dominant social group, face economic threats like wage reductions, unemployment, and social disruptions due to factors like automation shock, they perceive these not merely as personal threats but as threats to their group's status. It manifests as a collective sense of falling social esteem, a phenomenon that (Gidron & Hall, 2020) have conceptualized as a disruption in "social integration". White workers' anxiety over these economic shifts, combined with a demographic change wherein white dominance is waning, can push them towards seeking more stringent conformity from minority groups, aiming to reinstate their perceived loss of status. This also pushes these affected individuals to solidify their group affiliations, thus highlighting racial identities. Lastly, in the face of economic shocks, individuals often seek someone to blame, and this can manifest as animosity toward out-groups, further stoked by opportunistic political narratives. When long-term economic disruptions like those from trade shocks occur, they embolden latent biases, allowing them to be publicly expressed. Automation shocks might trigger similar pathways, leading to racial resentment among white workers.

The analysis leads to the following hypothesis:

Hypothesis 1*: White workers in local communities who experience a higher level of automation shock will exhibit a higher level of racial resentment.*

3.3.2 Automation and Affective Polarization

As automation disrupts traditional manufacturing job markets, white workers, often seeing themselves as part of a historically dominant group, may interpret this not just as personal economic upheaval but as an erosion of their collective social stature. This perceived loss of social esteem, rooted deeply in the social identity theory, can lead to heightened in-group affiliation, pushing white workers closer to political ideologies or parties that echo their anxieties and frustrations. Concurrently, these economic disruptions drive individuals towards seeking greater certainty in their group affiliations, further solidifying partisan lines. Furthermore, in times of economic distress, there's an increased tendency to blame external entities, potentially other political groups, or demographics. As partisan affective polarization is measured as the difference between in-party feeling and out-party feeling, the above dynamics can lead to more polarized party politics, with automation shock serving as a catalyst for entrenched partisan divides and heightened animosity between groups.

The analysis leads to the following hypothesis:

Hypothesis 2*: White workers in local communities who experience a higher level of automation shock will exhibit a higher level of partisan affective polarization.*

3.3.3 Automation and Public Support for Liberal Policies

Automation, specifically in the form of deindustrialization, decreases public support for liberal redistribution policies for two primary reasons: perceptions of fairness and shifts in societal values. Firstly, the American viewpoint tends to emphasize personal effort and the possibility of social mobility, suggesting that individuals can and should change their economic status through hard work alone. This belief system undermines the justification for redistributive policies. In the U.S., racial diversity, and associated tensions further complicate attitudes toward redistribution.

especially among the white working class who might view such policies as disproportionately benefiting other racial groups (A. Alesina & Angeletos, 2005). For dominant whites in the US, as a historically privileged group, they might perceive automation not only as a personal economic threat but also as a challenge to their social standing. Consequently, instead of rallying for redistribution, they might prioritize preserving their socio-economic dominance, possibly by resisting policies that seem to benefit out-groups or those they perceive as external threats. Secondly, Inglehart (1977) theory on the evolution of values postulates that as societies become more post-industrial, they experience a shift from materialistic values, which emphasize economic security and hence support redistributive policies, to post-materialistic values, which prioritize autonomy, self-expression, and quality of life. As economic stability becomes taken for granted, the support for redistributive policies wanes since individuals focus more on personal fulfillment than on material needs.

The analysis leads to the following hypothesis:

Hypothesis 3*: White workers in local communities who experience a higher level of automation shock will be less likely to support liberal policies on redistribution.*

3.4 Research Design

To examine the proposed hypotheses around the impact of automation shock on individual attitudes, I have developed three econometric models that operate at the Commuting Zone-individual level. A Commuting Zone within the United States is defined as a region encompassing multiple counties, closely interconnected through economic and social ties. The primary independent variable under investigation is the automation shock, measured by the change in industrial robot utilization within these zones from 1993 to 2007 (Acemoglu and Restrepo 2022). The dependent variables include individual-level attitudes sourced from a range of surveys conducted after the identified period of automation intensification: racial resentment drawn from the Cooperative Election Study (CCES) datasets of 2008, 2010, and 2011; partisan affective polarization from the National Annenberg Election Studies (NAES) 2008 wave; and attitudes towards liberal redistributive policies from the 2016 CCES. The focus is specifically on white workers, based on the theoretical prediction of a racial identity backlash in response to automation-induced economic disruptions across U.S. communities.

For each econometric model, survey respondents are matched to their respective Commuting Zones using county FIPS codes, ensuring that the analysis accounts for local economic conditions. To mitigate the potential endogeneity in the relationship between automation shock and the dependent variables—which could be influenced by other domestic factors rather than the automation per se—I employ an instrumental variable strategy akin to the shift-share approach used by Acemoglu and Restrepo (2022). The instrument of choice for this model is the change in automation exposure in five comparable advanced European economies over the same period. This strategy is predicated on the notion that the advancement of automation in these countries is largely a result of their own technological development trajectories and not driven by the labor market conditions of the United States. This approach provides a more robust inference by isolating the exogenous variation in automation exposure from other local shocks that could confound the observed relationships.

3.4.1 Dependent Variables

Racial Resentment

I will utilize the racial resentment metric, as outlined by Kinder and Sears (1981) and Acharya et al. (2016), from the Cooperative Election Study (CCES) dataset. In alignment with the approach of Acharya et al. (2016), I pool CCES survey data from 2008, 2010, and 2011. The 2010 survey includes two distinct questions. The first question asks respondents, on a five-point scale, about their agreement with the statement: “The Irish, Italian, Jews and various other minorities overcame prejudice and ascended socially. Blacks should follow suit.” The subsequent question gauges agreement, on the same scale, with the assertion: “Historical slavery and discrimination have established circumstances that challenge Blacks’ ability to rise from the lower class.” (CCES, 2008, 2010). The 2011 CCES repeats the first question from 2010. I rescale it to range from 0 to 1, a higher value means a higher level of racial resentment.

Affective Polarization

Following Lelkes et al. (2017), affective polarization is measured through feeling thermometer surveys. Within the National Annenberg Election Studies (NAES) dataset, respondents indicate their sentiments towards both their affiliated party or candidates and opposing parties or candidates using a 10-point scale. A higher score denotes more positive feelings. Affective polarization is quantified by determining the difference between in-party and out-party thermometer readings. This method stands as the predominant approach to measuring affective polarization in contemporary research. I also rescale it to range between 0 and 1, with a higher value indicating a higher level of affective polarization following previous practice.

Support for Liberal Policies

This data comes from the 2016 CCES dataset. In this dataset, people were asked their views on various policy areas like minimum wages, government spending on welfare, healthcare, and education. If someone supports a policy, it's marked as “1”, and if they don't, it's “0”. The full dataset has entries from 62,590 individuals across 2,236 counties. However, since my main interest is in understanding the perspectives of white individuals, I'm focusing on a subset that has 43,320 entries from 2,175 counties.

3.4.2 Independent Variables and Instrumental variables

Following Acemoglu and Restrepo (2018, 2019, 2022), I measure exposure to automation on the commuting zone level. A commuting zone is defined as an area with close economic ties and labor market ties. It is larger than counties in most cases because counties are not suited to define a local market. It is widely used in economic and social analysis. Their equation for the automation shock basically tracks the employment of industrial robots in different examined industries and concerned countries over time, in this case, the US from 1993 to 2007 and measures how the output of these industries has grown and compare it with the initial levels of employment within the industries. The main instrumental variable is using the same equation, but it is a shift-share measure of five European countries instead of the US: Denmark, Finland, France, Italy, and Sweden. They exclude Germany because Germany is not ahead of the US on automation.

3.4.3 Controls

For each analytical model, I include control variables at both the regional and individual levels to account for potential confounding factors. At the regional level, I utilize a range of indicators from the ICPSR County Characteristics data covering the period from 2000 to 2007. These indicators encompass various demographics and socio-economic factors, such as median age, percentages of black and white populations, census regional classifications, levels of educational attainment, median household incomes, population densities, and gender ratios. Additionally, to account for deep-seated cultural factors that could influence racial resentment, I incorporate historical data on the proportion of slaves present in each county as of 1860, as outlined in the methodology of Acharya et al. (2016). At the individual level, I control for characteristics including, but not limited to, the respondent's age, level of education, gender, and political affiliations. Table 8 shows the definitions of the variables used in these models.

Table 3-1. Variable definitions

Variable	Definitions
Automation	A 20-year change measurement on US CZs' exposure to robots 1993-2007;
Black Population	Black population number on the county level, logged;
Slave 1860	Percentage of slaves on the county level in 1860;
White/Black Income Ratio	The ratio between white and black people's average income level;
Edu Cut	A 6-category cut for individual education levels;
Religion	Whether respondent is a church goer;
Income Cut	A 5-category cut on individual income levels;
Female	A dummy variable on the sex of respondent;
Age	Age of respondent in the year examined;
Republican/Party ID	Party affiliation;
Unemployment	County level unemployment rate;
Internet Providers	Number of internet providers on the county level, logged;
Income	Individual level income, continuous variable;
Region	A 5-Category variable on regions in the US;
Black percentage	Percentage of black population on the county level;
White percentage	Percentage of white population on the county level;
Male percentage	Percentage of male on the county level;
Low edu county	Counties with lower-than-average education rate;
Population density	Population density on the county level;
Anti-immigration	A 5-category variable on individual's anti-immigration levels;
Family Econ Worse	A dummy variable on whether one feels his/her family experience worse economic situations;
Family income	Family income level in the past four years;
Unemployed	A dummy variable on whether the person is unemployed;
Foreign born change 00-14	The rate change of foreign-born population on the county level;
Union member	A dummy variable on whether one is a union member;
College	A dummy variable on whether one has a college degree;
Racial attitudes	A 5-category variable on the level of one individual's conservative racial attitudes;

3.5 Empirical Results

3.5.1 Results on Racial Resentment

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 3-1. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max	
Trade Shock	704	0	3.5	2.5	0.0	3.1	49.0	
Automation Shock	704	0	0.3	0.7	−3.7	0.3	6.1	
Racial Resentment	10	46	3.8	1.2	1.0	4.0	5.0	
Black Proportion	14495	11	0.1	0.1	0.0	0.0	1.0	
Slave Percentage 1860	1176	7	0.1	0.2	0.0	0.0	0.9	
White/Black Income Ratio	2524	1	1.5	0.4	0.2	1.5	10.5	
Unemployment	2832	0	0.1	0.0	0.0	0.1	0.2	
Female	2	0	0.5	0.5	0.0	1.0	1.0	
Age	79	0	52.1	15.4	18.0	54.0	96.0	
Republican	2	0	0.5	0.5	0.0	0.0	1.0	

Figure 3-2. Categorical variables

		N	%
Republican	0	49740	53.3
	1	43581	46.7
Female	0	45531	48.8
	1	47790	51.2
Income cut	<20k	9069	9.7
	100-150k	11401	12.2
	150k+	8931	9.6
	20-50k	27259	29.2
	50-100k	30472	32.7

I fit an OLS and IV model with commuting zone fixed effects. The IV model (table 3-3) results show that automation has a positive effect on racial resentment, however, it is not statistically significant. It means that the evidence does not support racial resentment as the mechanism that automation shock affects the rise of right-wing populism in the US. However, it should not be interpreted as that labor market reshuffling does not have any effect on racial attitudes. It's just that automation-induced manufacturing job displacement alone can't explain the rise of racial resentment among the dominant whites in the US.

There are some limitations to these models as well: the sample is confined to three CCES waves: 2008, 2010, and 2011, immediately after the examined automation shock period from 1993 to 2007. Later years might show bigger effects. It might also be possible that the measurement of automation cannot fully capture the effect of automation on the local communities.

Table 3-2. OLS model on automation and racial resentment

Automation and Racial Resentment	
	Dependent variable:
	Racial Resentment
Automation	0.187
	(2.310)
Black Percentage	-0.230***
	(0.051)
Slave Percentage 1860	0.267***
	(0.097)
White/Black Income Ratio	-0.042***
	(0.015)
High School	0.021
	(0.038)
Some College	-0.262***
	(0.038)
2-year College	-0.168***
	(0.041)
4-Year College	-0.537***
	(0.038)
Postgrad	-0.816***
	(0.040)
Religion	0.237***
	(0.012)
Income(100-150k)	-0.092***
	(0.023)
Income(150k+)	-0.035
	(0.025)
Income(20-50k)	-0.016
	(0.019)
Income(50-100k)	-0.061***
	(0.020)
Female	-0.041***
	(0.011)
Age	-0.002***
	(0.0004)
Republican	0.959***
	(0.012)
Intercept	3.938***
	(1.032)
CZ Fixed effects?	Yes
Observations	37,531
Adjusted R^2	0.276
Residual Std. Error	1.026 (df = 37010)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 3-3. Instrumental variable model on automation and racial resentment

Automation and Racial Resentment	
	Dependent variable:
	Racial Resentment
Automation	0.010
	(0.017)
Black Percentage	-0.211***
	(0.049)
Slave Percentage 1860	0.130**
	(0.059)
White/Black Income Ratio	-0.020
	(0.013)
High School	0.013
	(0.038)
Some College	-0.272***
	(0.038)
2-year College	-0.170***
	(0.041)
4-Year College	-0.552***
	(0.038)
Postgrad	-0.830***
	(0.040)
Religion	0.249***
	(0.012)
Income(100-150k)	-0.112***
	(0.023)
Income(150k+)	-0.054**
	(0.025)
Income(20-50k)	-0.023
	(0.019)
Income(50-100k)	-0.076***
	(0.019)
Female	-0.039***
	(0.011)
Age	-0.002***
	(0.0004)
Republican	0.966***
	(0.011)
Intercept	3.914***
	(0.070)
CZ Fixed effects?	Yes
Observations	37,531
Adjusted R^2	0.271
Residual Std. Error	1.029 (df = 37471)
Note:	*p<0.1; **p<0.05; ***p<0.01

3.5.2 Results on Affective Polarization

Figure 3-3 and figure 3-4 show the descriptive statistics for all the variables used in the models in this part. I include the histogram of all the continuous variables.

Figure 3-3. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
Trade Shock	690	0	3.6	2.7	0.0	3.1	49.0
Automation Shock	690	0	0.4	0.7	−3.7	0.3	6.1
Affective Polarization	865	14	0.3	0.3	−1.0	0.2	1.0
Black Percentage	2762	0	0.1	0.1	0.0	0.1	0.9
White Percentage	2769	0	0.8	0.1	0.1	0.9	1.0
Male Rate	2765	0	0.5	0.0	0.4	0.5	0.7
Internet Providers	961	0	10.7	3.3	2.7	10.5	20.7
Unemployment	105	1	5.0	1.3	1.9	4.9	16.0

The model on automation and affective polarization is also a commuting zone fixed effect model. The IV model results (Table 3-4) show that automation has a negative but statistically non-significant effect on partisan affective polarization. The negative coefficient means that affective polarization is less likely than racial resentment to be the mechanism that automation shock leads to right-wing populism in the US. However, it is worth noting that the dependent variable was measured in 2008 when partisan affective polarization was not the fiercest in the US. This result also does not mean that local automation-led labor market reshuffling does not have any effect on partisan psychological dynamics in the US.

Figure 3-4. Categorical variables

		N	%
Party ID	Democrat	20019	43.9
	Republican	20677	45.3
Female	Female	26107	57.3
	Male	19493	42.7
Age cut	Age: 1st Quartile	10226	22.4
	Age: 2nd Quartile	10858	23.8
	Age: 3rd Quartile	12715	27.9
	Age: 4th Quartile	11403	25.0
	Age: Missing	398	0.9
Income cut	Income: 1st Quartile	9728	21.3
	Income: 2nd Quartile	13926	30.5
	Income: 3rd Quartile	6280	13.8
	Income: 4th Quartile	10122	22.2
	Income: Missing	5544	12.2
Region	1: Northeast	9004	19.7
	2: Midwest	12492	27.4
	3: South	15220	33.4
	4: West	8770	19.2

Table 3-4. OLS model on trade shock and affective polarization

Automation and Affective Polarization

	Dependent variable:
	Affective Polarization
Automation	0.088
	(0.067)
Unemployment	-0.004***
	(0.002)
Internet Providers	-0.0003
	(0.007)
Republican	0.107***
	(0.002)
Female	-0.006***
	(0.002)
Age 4th Quartile	0.021***
	(0.003)
Some College	-0.008***
	(0.002)
Income 4th Quartile	0.008***
	(0.003)
Midwest	0.044**
	(0.022)
South	0.027
	(0.023)
West	0.054
	(0.049)
Black Percentage	0.053
	(0.034)
White Percentage	0.037
	(0.031)
Male Percentage	-0.094
	(0.102)
Low Education County	-0.003
	(0.005)
Population Density	0.034**
	(0.016)
Intercept	0.468***
	(0.099)
CZ Fixed effects?	Yes
Observations	39,108
Adjusted R^2	0.107
Residual Std. Error	0.165 (df = 38400)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Note: This is an OLS model, Certain variables have been omitted for brevity.

Table 3-5. Instrumental variable model on automation and affective polarization

Automation and Affective Polarization	
	Dependent variable:
	Affective Polarization
Automation	-0.163
	(0.495)
Unemployment	-0.004**
	(0.002)
Internet Providers	-0.003
	(0.008)
Republican	0.107***
	(0.002)
Female	-0.006***
	(0.002)
Age 4th Quartile	0.021***
	(0.003)
Some College	-0.008***
	(0.002)
Income 4th Quartile	0.008***
	(0.003)
Midwest	0.044**
	(0.022)
South	0.027
	(0.023)
West	0.054
	(0.049)
Black Percentage	0.044
	(0.039)
White Percentage	0.029
	(0.036)
Male Percentage	-0.100
	(0.103)
Low Education County	-0.003
	(0.005)
Population Density	0.034**
	(0.016)
Intercept	0.578**
	(0.236)
CZ Fixed effects?	Yes
Observations	39,108
Adjusted R^2	0.107
Residual Std. Error	0.165 (df = 38400)
Note:	*p<0.1; **p<0.05; ***p<0.01
	Note: This is an Instrumental Variable model, Certain variables have been omitted for brevity.

3.5.3 Results on Public Support for Liberal Policies

Figure 3-5 and figure 3-6 show the descriptive statistics for all the variables used in the models in this part. I include the histogram of all the continuous variables.

Figure 3-5. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
Minimum Wage	3	0	0.7	0.5	0.0	1.0	1.0
Welfare	3	44	0.3	0.5	0.0	0.0	1.0
Healthcare	3	41	0.8	0.4	0.0	1.0	1.0
Education	3	38	0.9	0.4	0.0	1.0	1.0
Trade Shock	668	0	3.5	2.5	0.0	3.1	49.0
Automation Shock	668	0	0.3	0.7	−3.7	0.3	6.1
Conservative Racial Attitudes	22	13	0.3	0.2	0.0	0.3	1.0
Age	79	0	50.0	16.9	18.0	52.0	98.0
Unemployment	2557	0	74.2	48.2	−87.7	73.5	358.6
Foreign born change	2505	0	56.3	56.6	−100.0	42.5	1100.0
Female	2	0	0.5	0.5	0.0	1.0	1.0
Latino Percentage Change 00-14	2518	0	97.9	69.8	−100.0	84.2	1684.0
Family Econ Worse	6	0	0.5	0.3	0.0	0.5	1.0
Relative Deprivation	3	10	0.6	0.5	0.0	1.0	1.0
Manufacturing job change 00-14	2557	0	−26.0	12.6	−90.1	−27.2	216.0
Anti-immigration	5	0	0.5	0.4	0.0	0.5	1.0
Union Member	4	0	1.5	0.7	1.0	1.0	3.0
Conservative Ideology	5	0	3.1	1.1	1.0	3.0	5.0
College	2	0	0.4	0.5	0.0	0.0	1.0
South	2	0	0.3	0.5	0.0	0.0	1.0
Family Income	13	10	6.4	3.2	1.0	6.0	12.0
Unemployed	2	0	0.0	0.2	0.0	0.0	1.0

Figure 3-6. Categorical variables

Party ID	N	%
Democrat	14142	31.8
Independent	17425	39.1
Republican	12929	29.0
NA	13	0.0

The results on automation and public support for liberal policies are mixed. Table 3-7 shows the IV model results. Automation does have a negative and statistically significant effect on public support for spending on welfare among whites, and the effect is not big, one unit increase in automation shock would increase the probability of supporting increasing government spending on welfare by 1.3 percent. This provides partial evidence for hypothesis 3b. However, the coefficients on healthcare and education are all positive and non-significant. The coefficient on public support for minimum wage is negative and non-significant. It might be possible that white workers hit by automation shock might have different views on different public spending schemes. It might also be possible that automation alone cannot incentivize enough grievances and that racial divisions are not activated.

Table 3-6. OLS models on trade and public support for liberal policies

Automation and Support for Liberal Policies

	Dependent variable:			
	Minimum Wage	Welfare	Healthcare	Education
	(1)	(2)	(3)	(4)
Automation	0.001	0.003	0.001	-0.001
	(0.004)	(0.005)	(0.005)	(0.004)
Racial Attitudes	-0.407***	-0.415***	-0.476***	-0.403***
	(0.012)	(0.013)	(0.013)	(0.011)
Anti-immigration	-0.141***	-0.206***	-0.097***	-0.074***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Econ Worse	-0.083***	-0.060***	-0.079***	-0.088***
	(0.009)	(0.011)	(0.010)	(0.009)
Unemployment	-0.00001	-0.0002**	-0.0002***	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Family Income	-0.016***	-0.026***	-0.019***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	0.066***	0.103***	0.023*	-0.006
	(0.011)	(0.013)	(0.012)	(0.010)
Foreign-born Change (00-14)	0.00003	0.0001	0.00003	0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Union Member	0.014***	0.003	0.005	0.008***
	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.027***	-0.064***	0.033***	0.050***
	(0.004)	(0.005)	(0.005)	(0.004)
Conservative Ideology	-0.086***	-0.096***	-0.070***	-0.040***
	(0.003)	(0.003)	(0.003)	(0.003)
South	0.009	0.075***	-0.016	0.001
	(0.023)	(0.026)	(0.024)	(0.022)
College	-0.080***	0.031***	-0.069***	-0.049***
	(0.005)	(0.006)	(0.005)	(0.004)
Age	0.001***	-0.001***	0.001***	-0.001***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Independent	-0.109***	-0.172***	-0.080***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.005)
Republican	-0.172***	-0.190***	-0.121***	0.006
	(0.007)	(0.008)	(0.007)	(0.006)
Intercept	1.261***	1.321***	1.422***	1.337***
	(0.036)	(0.040)	(0.037)	(0.033)
CZ Fixed effects?	Yes	Yes	Yes	Yes
Observations	34,550	22,247	23,357	24,616
Adjusted R^2	0.304	0.437	0.328	0.218
Residual Std. Error	0.398 (df = 34483)	0.359 (df = 22180)	0.343 (df = 23290)	0.304 (df = 24549)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Note: This is an OLS model, Certain variables have been omitted for brevity.

Table 3-7. IV models on trade and public support for liberal policies

Automation and Support for Liberal Policies

	Dependent variable:			
	Minimum Wage	Welfare	Healthcare	Education
	(1)	(2)	(3)	(4)
Automation	-0.011	-0.013*	0.003	0.006
	(0.007)	(0.008)	(0.007)	(0.006)
Racial Attitudes	-0.407***	-0.415***	-0.476***	-0.403***
	(0.012)	(0.013)	(0.013)	(0.011)
Anti-immigration	-0.141***	-0.206***	-0.097***	-0.074***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Econ Worse	-0.083***	-0.061***	-0.079***	-0.088***
	(0.009)	(0.011)	(0.010)	(0.009)
Unemployment	0.00000	-0.0001**	-0.0002***	-0.0001*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Family Income	-0.016***	-0.026***	-0.019***	-0.008***
	(0.001)	(0.001)	(0.001)	(0.001)
Unemployed	0.066***	0.103***	0.023*	-0.006
	(0.011)	(0.013)	(0.012)	(0.010)
Foreign-born Change (00-14)	0.00003	0.0001	0.00003	0.00001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Union Member	0.014***	0.004	0.005	0.007***
	(0.003)	(0.003)	(0.003)	(0.003)
Female	0.027***	-0.064***	0.033***	0.050***
	(0.004)	(0.005)	(0.005)	(0.004)
Conservative Ideology	-0.086***	-0.096***	-0.070***	-0.040***
	(0.003)	(0.003)	(0.003)	(0.003)
South	0.007	0.072***	-0.016	0.002
	(0.023)	(0.026)	(0.024)	(0.022)
College	-0.080***	0.031***	-0.069***	-0.049***
	(0.005)	(0.006)	(0.005)	(0.004)
Age	0.001***	-0.001***	0.001***	-0.001***
	(0.0001)	(0.0002)	(0.0002)	(0.0001)
Independent	-0.109***	-0.172***	-0.080***	-0.033***
	(0.006)	(0.007)	(0.006)	(0.005)
Republican	-0.173***	-0.190***	-0.121***	0.007
	(0.007)	(0.008)	(0.007)	(0.006)
Intercept	1.269***	1.332***	1.421***	1.332***
	(0.036)	(0.040)	(0.037)	(0.033)
CZ Fixed effects?	Yes	Yes	Yes	Yes
Observations	34,550	22,247	23,357	24,616
Adjusted R^2	0.303	0.437	0.328	0.218
Residual Std. Error	0.398 (df = 34483)	0.359 (df = 22180)	0.343 (df = 23290)	0.304 (df = 24549)
Note:				*p<0.1; **p<0.05; ***p<0.01

Note: This is an Instrumental Variable model, Certain variables have been omitted for brevity.

3.6 Conclusion

In this chapter, I construct a theoretical framework linking automation shocks to white identity politics, marked by racial divisions and partisan affective polarization. Additionally, I investigate the capacity of redistributive policies to mitigate the impact of automation shocks on the surge of right-wing populism. I examine two hypothesized mechanisms—social identity and the policy-driven need for compensation—to assess their roles in fostering right-wing populist sentiments in the wake of automation shocks. Contrary to common assumptions in the literature, the evidence suggests that neither identity politics nor policy compensation act as mediators in the expected ways. This calls into question the potency of automation shock as a solitary force in sparking identity politics or demands for redistributive action.

The absence of micro-level support for a direct link between automation shocks and right-wing populism hints that the association seen at the macro level may not be causal but rather a complex interplay of factors. Research on automation shock encounters challenges similar to those in trade shock literature: an indirect effect on negative political outcomes via labor market disturbances without a direct effect on political attitudes, and a disconnection between the studied dependent variables and the actual impact of automation, where issues directly related to automation have low political salience despite clear automation cues.

These insights cast doubt on simplistic narratives that ascribe political behavior and trends solely to automation shocks. Consequently, the policy recommendations that emerge from this analysis suggest that countermeasures to dampen political unrest should not be narrowly focused on automation-specific regulations. A more expansive strategy, possibly integrating labor market reforms, educational and skill enhancement programs, and broader economic adjustments.

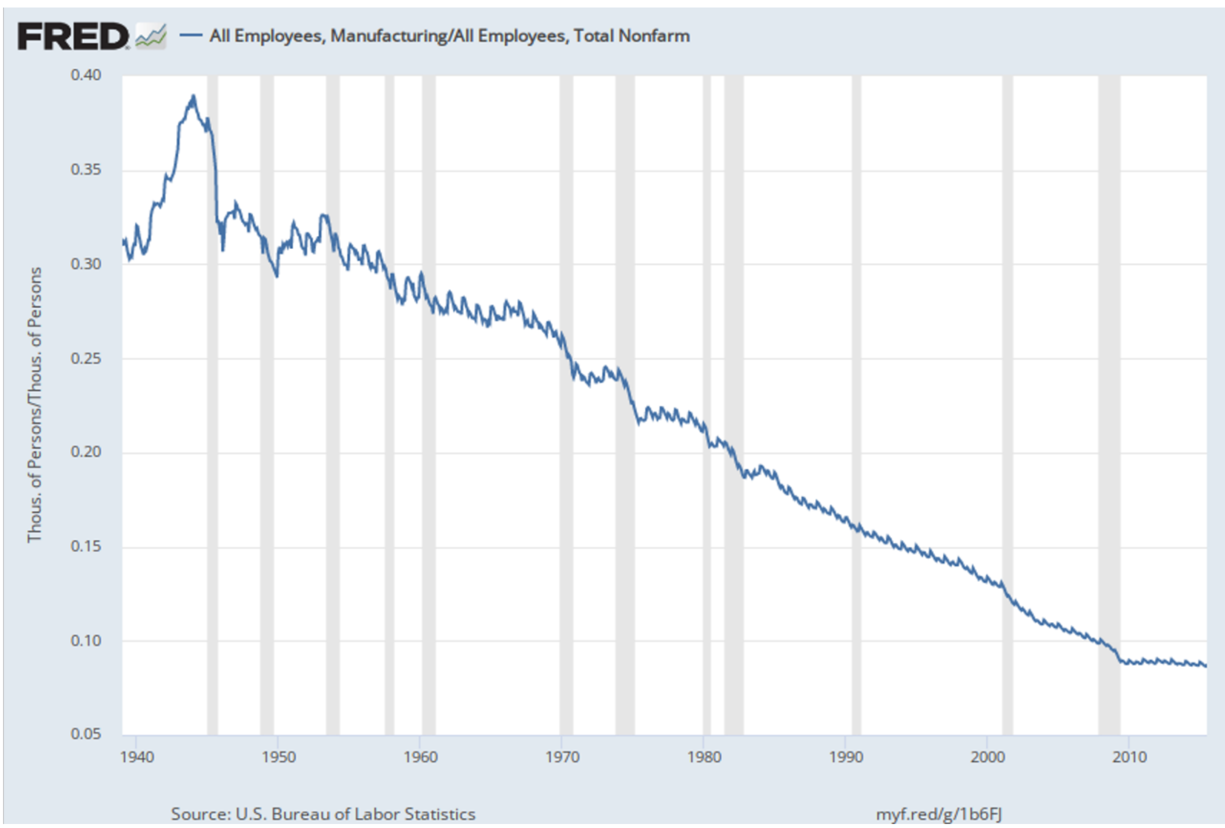
CHAPTER 4: DEINDUSTRIALIZATION, IDENTITY POLITICS, AND PUBLIC SUPPORT FOR LIBERAL POLICIES

4.1 Introduction

Manufacturing jobs have been decreasing heavily in the US since the 1940s (as shown in figure 4-1). Both trade shock and automation shock contribute to the decline of manufacturing jobs in the US. However, trade shock and automation shock do not have statistically significant effects on affective polarization, racial resentment, or support for liberal policies. The main reason that individual-level evidence is lacking is that previous studies examine trade shock or automation shock separately, instead, I argue in this chapter that deindustrialization as a whole, regardless of its sources, is the main driver for negative identity politics in the US. The focus on manufacturing jobs not unemployment in general is because service jobs are increasing (Fort et al. 2018), therefore unemployment alone cannot fully capture the scale of structural economic change in the manufacturing sector.

In addition to examining the two primary sources of deindustrialization separately and indirectly, we should also examine the whole effects and directly focus on the labor market, as voters are not always able to distinguish "which" or even "what" has caused the manufacturing layoffs, let alone forming clearly defined policy preferences and political attitudes based on their assessment of the weight of the different shocks. For example, previous research has shown that U.S. citizens often have limited knowledge about trade patterns and mechanisms, even within their nation (Rho & Tomz, 2017). In many cases, they will even misattribute the blame to one another (Gallego & Kurer, 2022; Wu, 2022, 2023). I follow the new development in the literature and argue that economic shock and cultural shock are not mutually exclusive (Baccini & Weymouth, 2021; Ballard-Rosa et al., 2021b, 2022; Bisbee, 2020; Bisbee & Rosendorff, 2021), it is an economic shock of identity backlash. I argue that deindustrialization or manufacturing layoffs is a more direct and better way of capturing the effect of labor market shock, it is more politically salient than mere trade and automation shocks. I complement the literature by testing the social identity mechanisms: affective polarization and racial division. I further test how deindustrialization affects voters' policy preferences on redistribution.

Figure 4-1. The share of manufacturing jobs from 1940 to 2010s, source: U.S. Bureau of Labor Statistics



The empirical analysis tests how manufacturing layoffs instead of unemployment affect affective polarization, racial resentment, and attitudes toward liberal policies. Using nationally representative survey data from the American National Election Studies (ANES) 2012, and 2016 waves and the Cooperative Election Study (CCES) 2016 wave, the empirical analysis tests whether county-level manufacturing layoffs–measured as a 4-year shift-share change of manufacturing jobs on the county level (Baccini & Weymouth, 2021), affect individual-level identity politics, thus examining the mechanisms that localized deindustrialization affect the rise of right-wing populism in the US. It mainly focuses on white people as the theory is a theory of "white backlash" to deindustrialization. It will also examine how minorities respond differently to non-white deindustrializations. Following previous literature, this chapter also adopts Bartik, (1991) instrumental variable research design, the instrumental variable is a 4-year shift-share change of national-level employment situations weighted by initial county-level manufacturing employment (Baccini & Weymouth, 2021).

The analysis has three main findings. First, it finds that county-level manufacturing layoffs do not have a statistically significant effect on partisan affective polarization for white workers, the signs of the coefficients are even negative. This result suggests that partisan affective polarization is not the main causal channel that deindustrialization affects right-wing populism. Second, county-level deindustrialization does have a positive impact on individual-level racial resentment of white people. This result suggests that racial resentment is one plausible channel through which deindustrialization contributes to the rise of right-wing populism. Third, county-level deindustrialization does have a negative and statistically significant effect on support for liberal policies like spending on welfare, education, health care, and minimum wages. It provides further evidence that racial resentment is one of the main causing mechanisms, as the normal reaction to economic suffering should be asking for more redistribution, for example, Scheve & Serlin (2023) find that the German trade shock in the 1920s led to the rise of modern welfare-state in the UK. Frieden (2019) argues that the backlash against globalization in the forms of voting for right-wing populist candidates like Trump is mainly due to "failure of representation", the main driver for it is the "failure of compensation", as the TAA program is very small and ineffective.

White voters who are suffering from deindustrialization do not have strong support for progressive candidates, instead, they are turning away from the Democrats and turning to right-wing populists. The turning of the white working class towards Republicans started in the 1970s when deindustrialization was accelerating (Abramowitz & McCoy, 2019). A last related finding is that for the non-whites, deindustrialization does not have a negative impact on support for redistribution.

This chapter contributes to at least three literatures. The first is the political consequences of trade shock and automation literature. In this study, I take a comprehensive approach and examine the total effect of trade and automation shock by focusing on deindustrialization as a whole. It informs the debate on whether it's the trade shock or automation shock that makes the bigger contributions to deindustrialization by directly examining the combined effect, regardless of its causes, as it's hard to clearly distinguish the two, and in many cases, they influence each other. When examining the political effects, separating the two might miss some important factors. Second, the economic shock vs. identity shock of right-wing populism literature. It informs the debate on trade/automation-led labor market shock vs. the cultural/identity shock on the rise of right-wing populism. It examines the causal mechanisms of the backlash against deindustrialization. It provides new individual-level evidence on the backlash literature. It also provides further evidence of why the backlash is mainly in the form of right-wing populism, only a small rise in the form of left-wing populism or redistribution. Third, the rise of negative identity politics literature, especially the racial polarization literature. Instead of viewing racial resentment as an exogenous variable that is pitted against the economic variables, this study finds that structural economic change contributes to the rise of the political salience of racial resentment in the US, echoing previous literature (Abramowitz & McCoy, 2019).

The rest of this chapter is structured as follows: the next section reviews the relevant literature on the debate on trade shock and automation shock; part three lays out the theoretical explanations on deindustrialization and racial resentment, deindustrialization, and attitudes towards liberal policies/redistributions. Part four is the research designs and data sources. Part five presents the results. The final part concludes with discussions.

4.2 Literature Review

Two literatures are related to the topic in this chapter. The first body of literature is the debate on whether trade shock or automation shock makes a bigger contribution to manufacturing layoffs and whether it is empirically possible to differentiate the two. The second strand of literature is whether voters are savvy enough to know the subtleties of different sources of shocks and whether the two are politically salient.

4.2.1 Automation Shock vs. Trade Shock’s Effect on the Labor Markets

Scholars are debating whether trade shock or automation shock are the main drivers of labor market displacement. On the one hand, one body of research argues that it is the trade shock, especially the trade shock from China that makes a greater contribution to labor market reshuffling. Autor et al. (2015) try to disentangle the effects of trade and automation. They found that trade challenges notably lead to substantial reductions in local manufacturing jobs, spurring increases in unemployment and non-employment, particularly among non-college-educated workers. In contrast, technological shifts don't necessarily diminish overall employment; instead, they cause a pronounced shift in the nature of jobs. Over time, the effects of trade become more pronounced, especially with the rise of imports from China, while the technological impact on manufacturing slows, but intensifies in knowledge-based sectors.

On the other hand, others argue that technology has distributional effects on labor markets, leading to what (Keynes, 1931) termed "technological unemployment." Technology has been a primary factor behind job declines since the post-WWII era, independent of trade variations (Edwards & Lawrence, 2013). For example, the introduction of mini-mills in the U.S. steel sector boosted production but led to job losses (Collard-Wexler & De Loecker, 2015). Regions in the U.S. that more readily embraced robots saw greater employment reductions, indicating a direct link between automation and job loss (Acemoglu & Restrepo, 2020; Graetz & Michaels, 2017). Chiacchio et al. (2018) identified similar trends across six European nations, noting that automation reduces local employment but found no significant impact on wages. In contrast, research in Germany by Dauth (2018) using matched employer-employee data, revealed that displaced workers transitioning to higher-skill roles didn't significantly alter overall unemployment, but wage inequality rose. Lastly, Frey & Osborne (2017) forecast that in the next 20 years, 47% of US workers may be at high risk of job displacement due to automation. Moreover, the job market has grown increasingly polarized with more individuals in high-skill, high-wage roles and low-skill, low-wage service jobs, while middle-tier jobs are diminishing (Anelli et al., 2023; Goldin & Katz, 1998; Goos et al., 2014; Nordhaus, 2007).

However, the overlapping influences of trade and technology complicate our understanding of their individual contributions to economic changes. Owen (2019) directly breaks up the tasks of workers related to trade and automation. She shows the convergence and divergence on high-low trade shock and automation. Other scholars go even further and argue that it is extremely difficult to disentangle the effects of the two (Fort, 2017). Studies indicate that tech innovations could emerge due to trade fluctuations. Therefore, there is a reciprocal relationship between trade and technology. For example, businesses may change their products influenced by import pressures (Bernard et al., 2006, 2010; Khandelwal, 2010). European data shows firms enhancing tech infrastructure when confronted with Chinese imports (Bloom et al., 2016). Further, advancements in communication tech have been shown to facilitate trade (Fort, 2017; Steinwender, 2018). Mix findings in this research highlight the complexity of differentiating between trade and technology's roles in influencing manufacturing jobs. Some economists make the first attempt to examine the combined effect of trade shock and automation shock on local labor markets (Galle et al., 2021).

4.2.2 Workers' Knowledge of Automation Shock vs. Trade Shock and the Political Salience of the Two

Scholars also debate the political effects of each individual shock. Some argue that they are quite different. Mutz (2021b) finds that the American public mainly blames trade instead of automation for job loss. While some studies find that both automation and trade shock lead to protectionism (Naoi, 2020; Tella & Rodrik, 2020), most studies find that automation does not have any effect on redistribution (Gallego, Kuo, et al., 2022; Gallego & Kurer, 2022; Zhang, 2022), or even negative impact on tariffs and redistribution (Frieden, 2022; Naoi, 2020; Tella & Rodrik, 2020). This trend is also documented in several recent studies (Baccini & Weymouth, 2021; Chaudoin & Mangini, 2023). Baccini & Weymouth (2021) argue that the two shocks have differing political effects on right-wing populism because trade shock involves the social identity of out-groups. Some scholars emphasize the importance of the "foreignness" of the trade shock compared to the "nativeness" of the automation shock (Chaudoin & Mangini, 2023). Some new studies try to address the political salience disparities between the two shocks. The main explanation is "blame misattribution". Wu (2022) argues that people misattribute automation to trade. She finds that automation leads to higher levels of protectionism. In the same vein, Tella &

Rodrik (2020) find that automation leads to support for more tariffs. Wu (2023) further finds that automation leads to more support for tariffs among Democrats and anti-immigration among Republicans.

However, for workers, it shouldn't matter much as to which shock has caused the economic hardship, as the end results for individuals are the same loss of jobs and ensuing negative social suffering. Trade itself is a politically low-salience issue (Bisbee & Rosendorff, 2021; Guisinger, 2017; Rho & Tomz, 2017), workers in many cases are not knowledgeable enough to understand the difference between the two, thus the political salience of the two is hard to differentiate as well. Some scholars have started to examine the political consequences of the two shocks together. For example, Chaudoin & Mangini (2023) directly examine the "foreignness" of automation shock, they find that foreign automation can also have the potential to be politically salient. They further argue that economic nationalism and comparative advantage interact with each other to explain the phenomenon that populists respond less negatively towards automation than trade. Automation shocks also induce economic nationalism, comparative advantage also influences voters' attitudes.

Political scientists mainly examine these shocks separately, but the dependent variables they are trying to explain are similar to each other–mainly on the rise of right-wing populism in developed democracies. For example, the most often examined dependent variables are the vote share of Donald Trump and the vote share of Brexit at the local level. The theoretical frameworks are mainly based on the structural economic shock literature and surrounding two mechanisms: policy preferences and social identities (see Gallego and Kurer 2022 for a review). In most settings, trade shock and automation shock have an indirect effect on right-wing populism through their impact on the labor market.

These works raise important questions and provide some meso-level evidence to the economic backlash literature, however, there are at least two issues: First, while it is worthwhile to examine the effect of trade shock (especially trade shock from China) and automation shock separately, examining the two and other sources together can provide a fuller picture of labor market reshufflings and its political backlash. On the one hand, scholars are still debating which of the two makes the greater contribution to manufacturing job loss. It might be trade, technology, or both contribute to manufacturing job loss equally, but in many cases, it is extremely difficult to calculate which source is more important (Fort et al., 2018c; Gallego & Kurer, 2022; Tyson, 2019). On the other hand, affected workers are not always able to understand which of the different sources contribute more to their job loss (Gallego & Kurer, 2022; Rodrik, 2018), in other words, the political salience of either trade or automation shock is extremely difficult to dissect. Second, the existing literature mainly examines the indirect effect of either trade or automation shock on politics through their impact on the labor market. The mechanisms in both literatures are very similar to each other. By focusing on deindustrialization–manufacturing layoffs directly, this paper can explore the direct effect of labor market reshuffling resulting from different sources on negative politics.

I examine the effects of trade shock and automation shock together and argue that examining the two sources of deindustrialization separately and indirectly might miss some important aspects, as affected white workers do not always have the knowledge to understand the different causes of their manufacturing job loss due to shuttered plants (Gallego & Kurer, 2022; Rodrik, 2018), focusing on one cause might miss the effect of another cause or the combined effect. Even economists and political scientists are not able to identify the two sources of deindustrialization (Fort et al., 2018c; Gallego & Kurer, 2022; Tyson, 2019). Some scholars make the first attempt to examine the combined effect of trade shock and automation shocks on local labor markets (Galle et al., 2021) and voting for right-wing populist candidates like Donald Trump (Baccini & Weymouth, 2021).

4.3 Theoretical Framework

I argue deindustrialization, regardless of its causes, will contribute to the rise of negative white identity politics and ensuing related policy preferences on redistribution. This research extends beyond the current discourse on whether right-wing populism's surge and its associated negative politics stem from economic or cultural backlash. Instead, I posit that it's an economic backlash manifesting as an identity backlash or activating the identity backlash (Bisbee & Rosendorff, 2021). In essence, the identity politics, racial resentment, and partisan affective polarization defining today's US politics are influenced by the lasting economic shifts stemming from deindustrialization (Abramowitz & McCoy, 2019; Colantone & Stanig, 2018b).

4.3.1 Deindustrialization and Workers' Perception of Self-Interest in the US

I argue that trade shock or automation shock alone cannot explain or invoke voters' identity crisis and voters generally do not care which have the bigger effect on the closure of the manufacturing plant which local communicates rely on. First, it's important to acknowledge that factors beyond trade and automation can lead to such closures. Mismanagement, shifts in demand, business cycles, financial crises, and other market forces also play crucial roles (Gomez & Wilson, 2001; Hellwig et al., 2008; Naoi, 2020). While trade and automation are significant contributors, they are far from being the only sources. Focusing exclusively on one factor can lead to an incomplete understanding and fail to isolate the causal impact of each element. Even if certain effects are identified, distinguishing whether they stem from these two factors or others becomes challenging, as the commonly used Commuting-Zone-Individual design may not adequately control for all variables.

Moreover, the complexity surrounding the causes of plant closures means that workers in affected communities often lack the necessary information to accurately pinpoint the origins of their predicaments, much less to form coherent policy responses. This lack of understanding, or "economic ignorance" (Bearce & Tuxhorn, 2017; Rho & Tomz, 2017), impairs people's grasp of their self-interest. Individuals with varying levels of knowledge may attribute their economic difficulties to different causes: those more informed might point to market forces, while others might blame elected officials, irrespective of the actual reasons (Hellwig et al. 2008; Naoi 2020). Scholars also note that the "political sophistication" of citizens influences their perceptions of personal and national economic conditions (Gomez and Wilson 2001, 2003).

However, given the intricate nature of manufacturing plant closures and job losses, even sophisticated economists and political scientists struggle to discern the most impactful factors, making it unrealistic for average workers to do so (Gallego and Kurer 2022). Workers experiencing plant closures often lack the economic and political knowledge needed to dissect the various causes of these closures and their personal economic challenges. As political economists debate these issues, workers' views may be shaped by other factors, such as social identities or political entrepreneurs who exploit their grievances by pointing fingers at common enemies—opposing political parties, immigrants, foreign nations, etc. This can lead to widespread misattribution of economic hardships to incorrect causes, policies, or groups. For instance, Wu (2022, 2023) finds that workers often incorrectly attribute plant closures and job losses to trade, when automation is the actual cause, leading communities affected by automation to paradoxically support protectionism.

Lastly, this chapter's broader focus on deindustrialization, rather than exclusively on trade or automation, is driven by both theoretical and methodological considerations. Since the seminal work of Autor et al. (2013) on trade shocks and Acemoglu and Restrepo (2022) on automation shock, the primary analytical unit has been the commuting zone—a region comprising several counties. While economically relevant, this approach might not capture the nuanced variations in political sentiments found within smaller areas, such as individual counties or towns. Ordinary workers are more likely to be concerned with the immediate effects on their own communities, rather than on events occurring miles away. This perspective underscores the necessity of adopting a more comprehensive approach to understand the socio-economic impacts of deindustrialization on local communities and their political ramifications.

4.3.2 Deindustrialization and White Identity Politics in the US

Deindustrialization disrupts the affected workers and the whole communities in heavily hit areas. For workers with similar skills and training, the salaries of manufacturing jobs are higher than those of the service sector (Krueger & Summers, 1988). When factories are shut down, employees who are laid off from manufacturing roles generally see a decrease in their earnings later (Baccini and Weymouth 2021). The negative impacts are not confined to the workers that are directly affected. After the shutting down of a plant, the whole community faces increasing distress and negative consequences (for example the Janesville story in Goldstein, 2017), as the negative impacts of import competition can be transmitted to other sectors as industries are interconnected via supply chains (Acemoglu et al. 2012).

The reason for the focus on whites is that whiteness is associated with certain racial and job privileges (Guisinger, 2017; Harris, 1993; Roediger, 1999). When these manufacturing jobs are disappeared or under threat, it contributes to feelings of diminished status and societal standing.

Thus, the whites are responding to the negative shock of deindustrialization differently from the non-whites as different social groups react differently to similar economic challenges (Baccini & Weymouth, 2021; Green & McElwee, 2019). I expect deindustrialization would lead to a white-identity backlash in the forms of racial resentment, partisan affective polarization, and related attitudes on redistribution.

In the previous chapters, I lay out the two mechanisms that can be used to explain the linkages: social identity and public policy. There are four sub-mechanisms in the social identity theory. The first mechanism is the dominant social status threat mechanism. It states that the white working class is facing a status threat as disruptions from the deindustrialization, along with the demographic change that the white population is declining, threaten their dominance in social status and racial hierarchy. The threat can be realistic, symbolic, or both (Bobo, 1983; Bobo & Hutchings, 1996; Bobo & Kluegel, 1993; Riek et al., 2006; Sherif & Sherif, 1969). They become much closer to their own groups and further away or even generate hostility towards out-groups. The second mechanism is scapegoating (Bursztyn et al., 2022a, 2022c; Wu, 2022). It suggests that deindustrialization prompts individuals to seek explanations for their economic hardship, often assigning blame to out-groups perceived as responsible for their predicament. By scapegoating others, such as immigrants, or specific racial and ethnic minority groups, individuals can find a target for their frustration, which in turn reinforces negative stereotypes and fosters hostility. This process serves to divert attention away from the systemic causes of economic disparities and perpetuates divisions within society. The third mechanism is the anxiety mechanism, which posits that trade shock generates a sense of insecurity and fear among affected individuals, who become increasingly concerned about their economic prospects and social standing. This heightened anxiety can lead to a heightened sense of in-group solidarity among white workers and an amplified distrust or aversion towards out-groups, as individuals seek to protect their interests and maintain control in an uncertain environment. The process is both reactive and proactive. The fourth mechanism is the frustration-aggression mechanism. The frustration-aggression mechanism posits that deindustrialization-induced economic and social hardship and job loss create a pervasive sense of frustration among affected individuals. When faced with these challenges, people may develop aggressive tendencies as a response to their unfulfilled needs and aspirations. This aggression can manifest in various forms, such as increased hostility toward out-groups or a heightened inclination towards politically extreme positions (Ballard-Rosa et al., 2021b, 2022).

In addition to the social identity framework, the second main mechanism is the request for policy compensation. White workers affected by deindustrialization would ask for redistribution through various policies. This logic is straightforward in classic political economy literature. However, as white workers are not only concerned about their own economic conditions, but they also care about their group's relative social standing compared to other groups. Deindustrialization therefore does not necessarily lead to more public requests for redistribution among the dominant whites.

4.3.3 Deindustrialization and Racial Resentment

Why does deindustrialization affect racial resentment in the US? In the burgeoning literature on the economic backlash, racial identity threat is implied and even the main driving force for the backlash from the white working class. However, they have yet to directly test this mechanism. Race is politically salient in some years, but it's not in some other times. But, even when it is deemed to be less politically salient, it is of vital importance in American politics. Some scholars even emphasize the "centrality of race" in American politics (Bobo & Hutchings, 1996; Hutchings & Valentino, 2004). Hutchings and Valentino (2004) find that race matters in almost all-important aspects of American politics. As deindustrialization worsens, affected white workers can easily divert their attentions to racial issues, whether strengthening their racial identity or divert their hatred towards minorities through the above mechanisms.

Taken together, the above analyses lead to the following hypothesis:

Hypothesis 1: *White workers in US counties with a higher level of manufacturing layoffs will exhibit a higher level of racial resentment.*

4.3.4 Deindustrialization and Affective Polarization

Why does deindustrialization contribute to the rise of affective polarization? The main reason is that partisan identity might be more politically salient than racial identity, based on a Pew (2019) survey, partisan identity is becoming more important a defining feature of American voters than racial identity. Thus, when facing the shock of deindustrialization, whites in the two parties would align more closely with each party and tend to scapegoat the opposite party for all the negative consequences. In other words, partisan identity to some extent replaced the white identity, as more white working class have been realigned with the Republican party since the 1970s (Abramowitz & McCoy, 2019).

Moreover, if racism is the main driver in many discussions on the backlash against globalization literature, there might be spillover effects to affective polarization. Race and partisan are two different identities, but studies on US politics have documented the close relationship between race and partisanship. In his book "Racial Realignment: The Transformation of American Liberalism, 1932–1965", Schickler (2016) provides a comprehensive review of how race and partisanship have interacted throughout U.S. history, with a focus on the period from 1932 to 1965. More recently, Tesler (2013, 2015) argues that depending on the availability of political information on race-related issues, racial attitudes help to polarize the electorate. He further argues that there is a “racialization of party identification”. In their book– “Identity Crisis: The 2016 Presidential Campaign and the Battle for the Meaning of America”, Sides et al. (2018b) examine the role of racial attitudes, identity, and partisanship in shaping the 2016 U.S. presidential election. It analyzes how issues of race and identity influenced voters' choices and party affiliations. In “White Identity Politics”, Jardina (2019) explores the rise of white identity politics in the United States and its impact on partisan behavior. It delves into how racial identity influences political attitudes, voting patterns, and the dynamics of racial polarization.

More directly, Westwood and Peterson (2022) find that race and partisanship are inseparable in US politics. Drawing the concept of “spreading activation”, they argue that the two social identities are “so enmeshed” in public perceptions, that things linked to one identity can affect attitudes and behaviors toward both identities. To be more specific, they argue and find strong empirical evidence that there is a *parallel updating* process, which means that events that could raise the salience of either one of the two social identities could affect the effect of both identities. That is if trade shock can raise the salience of racial identities, it would also raise the salience of partisan identities. Abramowitz and McCoy (2019) find that racial resentment contributes to the rise of affective polarization in the US and that racial resentment is helping to reshape the American electorates on partisanship alignment. Thus, it is also theoretically possible that deindustrialization, in general, would contribute to the rise of affective polarization.

However, all four mechanisms point to the importance of the white identity. I further argue that racial resentment among whites is more important a causal mechanism than partisan affective polarization. Racial resentment is a more direct response to the white identity backlash while partisan affective polarization is less of a direct response to the “whiteness” backlash. Moreover, the affective polarization conceptualization and the widely accepted measurement of it leave out a huge group of white workers–the independents. As a matter of fact, it is indeed the vote-switching of many independents that finally sealed the victory of Donald Trump in 2016 (Reny et al., 2019). Partisan affective polarization is mainly driven by out-party animosity (Druckman & Levendusky, 2019), especially Republican animosity toward the Democrats. Therefore, while racial resentment and partisan affective polarization are closely related, they are not necessarily the same in terms of serving as a causal mechanism towards the rise of right-wing populism.

Taken together, the above analysis leads to the following hypothesis:

Hypothesis 2: *White workers in US counties with a higher level of manufacturing layoffs will exhibit a higher level of partisan affective polarization. However, this effect should be less prominent than its effect on racial resentment.*

4.3.5 Deindustrialization, Racial Division, and Support for Liberal Policies

In this chapter, I argue that deindustrialization also leads to less public support for liberal policies. There are two main explanations for the link. The first is the perception of "fairness" (Alesina & Angeletos, 2005; Newman et al., 2022; Scheve & Stasavage, 2017), and the second is the post-material values changes (Inglehart, 1977).

Alesina's (2005) exploration into the disparities in welfare states between the U.S. and Europe offers insightful perspectives on the role of fairness and redistribution. The understanding of fairness is contingent upon context: Europeans tend to attribute income distribution to luck, whereas Americans often see it as the fruit of individual effort. Furthermore, the belief in high social mobility in the U.S. — the idea that with determination, one can climb the economic ladder — further dampens support for wealth redistribution. One core aspect of his work concerns the U.S.'s racial diversity and redistribution. In the US, racial diversity and racial tensions have inhibited the desire for redistribution, contrasting with historically more homogeneous European nations. Americans may be less willing to support redistributive policies if they believe the benefits go to those perceived as racially or culturally different from themselves (Newman, Reny, and Ooi 2018). Deindustrialization contributed to the rise of racial tensions in local communities. Although affected workers should be asking for more redistribution, the white working-class views redistribution differently. However, the views on public support for redistribution also depend on the specific policies. The support for educational spending would be higher than general welfare spending, as education is viewed as a nontraditional public spending (Iversen & Goplerud, 2018).

The second line of reasoning concerns the value changes linked to post-industrialization. Inglehart's seminal work, "The Silent Revolution" (1977), offers a compelling insight into the dynamics of value shifts in post-industrial societies. As societies transition from predominantly industrial to post-industrial frameworks, there is a corresponding evolution in public values from materialistic to post-materialistic. In industrial societies, where economic security is often uncertain, materialistic values prioritize economic growth and stability, with a strong inclination towards redistributive policies as a means of ensuring equitable welfare. However, with the rise of post-industrial societies, where a level of economic stability is typically achieved, there's a notable shift towards post-materialistic values. These values emphasize individual autonomy, self-expression, and quality of life over material needs. As these post-materialistic values take root, there is a potential attenuation in public support for redistribution. An emphasis on individualism over collectivism may lead to reduced solidarity and communal responsibility, thus dampening the collective appetite for redistributive policies.

Taken together, the above analysis leads to the following hypothesis:

Hypothesis 3: *White workers in US counties with a higher level of manufacturing layoffs will be less supportive of liberal policies.*

4.4 Research Design

To test the above hypotheses, I focus on the geographic variation of deindustrialization in US counties and match it with individual-level data on voter attitudes from nationally representative surveys.

4.4.1 Localized Deindustrialization

There are two primary sources of deindustrialization: globalization and automation. It is extremely difficult to distinguish the two for scholars as well as many voters with less knowledge about labor economics, this study will take a comprehensive approach and focus on localized manufacturing layoffs in general, regardless of the causes. The data on the localized deindustrialization comes from the replication file of Baccini and Weymouth (2021). The original data are from the Quarterly Workforce Indicators (QWI) of the US Census Bureau. This microdata is the most comprehensive data on US labor markets with detailed records on the demographics of workers and firm characteristics. Baccini and Weymouth (2021) calculate the county-level manufacturing layoffs yearly counts from 2004 to 2016. Based on this and the demographic information of workers, they can calculate white manufacturing layoffs per worker and non-white manufacturing layoffs per worker within each county within a certain period. This measurement of deindustrialization can capture the whole effects of both automation shock and trade shock on local labor markets.

4.4.2 Econometric Models

The first empirical model is the association between localized deindustrialization and individual attitudes toward racial resentment. The unit of analysis is county-individual. I match the ANES 2016 survey data with county-level deindustrialization data prior to 2016. In the robustness check models, I also include previous waves. This analysis uses the whole data but only includes the white respondents in the main model, as the theory is mainly based on a white backlash. There are 4270 respondents in 1268 counties. The white-only sample has 2911 observations in 992 counties. The baseline model is:

$$Racial\ \ Resentment_{ic} = \alpha_0 + \beta_1 Whie\ \ Manufacturing\ \ Layoffs + \mathbf{X_c}\zeta + \mathbf{Z_i}\theta + \delta_c + \epsilon_{ic} \tag{1}$$

where *Racial Resentment* comes from the ANES 2016 survey, it indicates worker *i* in county *c*'s level of racial resentment. Following Kinder & Sanders (1996), and (Banda & Cassese, 2022), I measure racial resentment based on four questions in the ANES dataset. The ANES (2016) dataset asks respondents to report on the Likert scale with the following four statements in 2016:

(1) "Irish, Italians, Jewish, and many other minorities overcame prejudice and worked their way up. Blacks should do the same without any special favors;"

(2) "Generations of slavery and discrimination have created conditions that make it difficult for Blacks to work their way out of the lower class;"

(3) "Over the past few years, Blacks have gotten less than they deserve;"

(4) "It's really a matter of some people not trying hard enough, if Blacks would only try harder, they could be just as well off as whites."

Combining these answers together, I rescale the responses to these statements into a standardized metric that ranges between 0 and 1. A higher score on this scale signifies greater racial resentment. The main independent variable is the *Manufacturing Layoffs*. Following Baccini and Weymouth (2021), these variable measures the total number of manufacturing job losses per manufacturing worker in that county from 2012 to 2015. It calculates the total number of manufacturing job losses between 2012 and 2015, divided by the total workforce in that county as of 2011. It also ranges from 0 to 1, with a higher value indicating a higher rate of manufacturing layoffs in a county. The vector $\boldsymbol{X_c}$ is all the county-level control variables. It includes unemployment, service sector layoffs (using the same method as the main independent variable), the share of people with a college education, and the share of non-white people in a county. Vector $\boldsymbol{Z_i}$ includes all the individual-level control variables: age, education, party identification, gender, and income. I also include county-fixed effects.

To account for the endogeneity issue, I also adopt a Bartik instrumental variable approach widely used in the trade shock literature and further developed by Baccini and Weymouth (2021). The Bartik tool measures how certain groups in a county were impacted between 2012 to 2015, especially in the manufacturing sector. It is used to understand the relationship between local job losses and broader national trends. This method evaluates job data for specific social groups within a county, comparing local manufacturing employment in 2011 to the broader U.S. context. It then considers national manufacturing job losses from 2012 to 2015, excluding the specific county being studied. Essentially, the Bartik tool from Baccini and Weymouth (2021) predicts county-level manufacturing job losses based on national trends and the industries prevalent in that county, ensuring local anomalies don't skew the results. An instrumental variable affects the dependent variable only through its effect on the independent variable. The main factor that's being looked at is the mix of industries each county started with. For the Bartik method to provide a clear cause-and-effect understanding, this mix of industries should only influence the final results through its impact on job losses.

The second model is on the association between localized deindustrialization and partisan affective polarization. The model is:

$$Affective\ \ Polarization_{ic} = \alpha_1 + \beta_2 Whie\ \ Manufacturing\ \ Layoffs + \mathbf{X_c}\zeta + \mathbf{Z_i}\theta + \delta_c + \epsilon_{ic} \tag{2}$$

where *Affective Polarization* is an individual-level measurement from the ANES 2016 wave. The ANES dataset asks respondents to rate their feelings towards the Democratic party and the

Republican party on a scale from 0 to 100. Following common practice in the literature (Iyengar et al. 2019), it is calculated by subtracting the out-party feeling thermometer score from the in-party feeling thermometer score. The resulting measurement ranges from 0 to 100. A voter with the highest level of affective polarization would be one with a 100-feeling thermometer to his/her own party, and a 0-feeling thermometer to the opposite party. As this measurement is on partisans, the independents are excluded from the samples. However, many recent developments in the literature focus only on the out-party feeling (for example Levendusky et al. 2019), as the out-party feeling is the main driver for the polarization, not so much the in-party feeling. They also try to develop an implicit measurement of it. $\boldsymbol{X}$ is a vector of county-level controls and $\boldsymbol{Z_i}$ is a vector of individual-level characteristics. I also include the county-level fixed effect. The main model also adopts the Bartick instrumental variable method by Baccini and Weymouth (2021).

The third model tries to estimate the association between localized deindustrialization and support for liberal policies. The model is:

$$Pr(Support\ Policy_k) = \alpha_{2'} + \beta_{3'} Whie\ \ Manufacturing\ \ Layoffs + \mathbf{X_c}\zeta + \mathbf{Z_i}\theta + \delta_c + \epsilon_{ic} \tag{3}$$

where *Pr(Support Policy)* is the probability that one respondent supports a certain liberal policy *k*. This data is from the CCES 2016 dataset. The CCES datasets ask respondents whether they “support minimum wages”, “government spending on welfare”, “government spending on healthcare”, and “government spending on education”. It is coded as “1” if one supports the policy in question, and “0” otherwise. There are 62,590 observations in 2236 counties in the original full dataset. As my theory mainly focuses on whites, the white-only sample has 43,320 observations in 2175 counties. $\boldsymbol{X_c}$ is the vector of county-level controls for county c, and $\boldsymbol{Z_i}$ is a vector of individual-level controls for respondent *i* in county *c*. I also include a county fixed effect.

Table 4-1. Variable definitions

Variable	Definitions
White Deindustrialization	A 4-year change measurement on white people's manufacturing job layoffs in US counties from 2012-2016;
Black Population	Black population number on the county level, logged;
Deindustrialization	A 4-year change measurement on the manufacturing job layoffs in US counties from 2012-2016;
White/Black Income Ratio	The ratio between white and black people's average income level;
Edu Cut	A 6-category cut for individual education levels;
Religion	Whether respondent is a church goer;
Income Cut	A 5-category cut on individual income levels;
Female	A dummy variable on the sex of respondent;
Age	Age of respondent in the year examined;
Republican/Party ID	Party affiliation;
Unemployment	County level unemployment rate;
Deindustrialization Service	Service job layoffs in US counties from 2012-2016;
Income	Individual level income, continuous variable;
Region	A 5-Category variable on regions in the US;
Black percentage	Percentage of black population on the county level;
White percentage	Percentage of white population on the county level;
Male percentage	Percentage of male on the county level;
Low edu county	Counties with lower-than-average education rate;
Population density	Population density on the county level;
Anti-immigration	A 5-category variable on individual's anti-immigration levels;
Family Econ Worse	A dummy variable on whether one feels his/her family experience worse economic situations;
Family income	Family income level in the past four years;
Unemployed	A dummy variable on whether the person is unemployed;
Foreign born change 00-14	The rate change of foreign-born population on the county level;
Union member	A dummy variable on whether one is a union member;
College	A dummy variable on whether one has a college degree;
Racial attitudes	A 5-category variable on the level of one individual's conservative racial attitudes;

4.5 Empirical Results

4.5.1 Models on Racial Resentment

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 4-2. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
White Deindustrialization	929	0	0.0	0.0	0.0	0.0	0.3
Non-White Deindustrialization	919	0	0.0	0.0	0.0	0.0	0.2
Deindustrialization	929	0	0.1	0.0	0.0	0.0	0.4
Racial Resentment	20	14	0.6	0.3	0.0	0.6	1.3
Unemployment	339	0	6.6	1.6	2.6	6.4	23.5
Non-White Share	929	0	0.2	0.1	0.0	0.2	0.7
College Share	929	0	0.2	0.1	0.1	0.2	0.5
Service	929	0	0.0	0.0	0.0	0.0	0.0
Income	6	2	3.0	1.1	1.0	3.0	5.0
Age	74	0	49.9	19.0	0.0	52.0	90.0

Figure 4-3. Categorical variables

Party ID	N	%
Democrats	1135	39.0
Independents	361	12.4
Republicans	1404	48.2

Table 4-2 shows the results of the models on racial resentment. Model 1 only includes the main predictor as a baseline model. Models 2 to 4 are instrumental variable estimates. In model 2, I only include the main predictor white manufacturing layoffs, county-level unemployment, and individual-level characteristics. In model 3, I include all the county-level controls but excluding service sector deindustrialization. Model 4 is the full model with all the county-level controls and individual-level variables. All three models are positive and statistically significant. These results provide strong support for hypothesis 1 white workers in counties with a higher level of manufacturing layoffs would exhibit a higher level of racial resentment. The effects are quite huge: for the main model 4, the estimated coefficient is 0.792, which means that one unit increase in county-level manufacturing layoffs would increase average racial resentment in that county by 0.792 points.

Table 4-2. Models on deindustrialization and racial resentment

Deindustrialization and Racial Resentment				
	Dependent variable:			
	Resentment			
	OLS		*instrumental variable*	
	(1)	(2)	(3)	(4)
White Deindustrialization	1.791***	0.981**	0.924***	0.913***
	(0.227)	(0.489)	(0.331)	(0.333)
Unemployment		0.006	-0.006*	-0.006*
		(0.007)	(0.003)	(0.004)
Percent College			-0.465***	-0.465***
			(0.100)	(0.101)
Non-White Percentage			0.007	0.005
			(0.046)	(0.049)
Deindustrialization Service				-0.238
				(2.808)
Income			-0.012***	-0.012***
			(0.005)	(0.005)
Female		0.002	-0.001	-0.001
		(0.010)	(0.010)	(0.010)
High School		0.123***	0.119***	0.119***
		(0.014)	(0.013)	(0.013)
Some College		0.110	0.087	0.083
		(0.074)	(0.071)	(0.075)
College and above		0.099***	0.098***	0.098***
		(0.012)	(0.011)	(0.011)
Independent		0.178***	0.186***	0.186***
		(0.017)	(0.016)	(0.016)
Republican		0.265***	0.283***	0.283***
		(0.011)	(0.010)	(0.010)
Age		0.001***	0.001***	0.001***
		(0.0003)	(0.0003)	(0.0003)
Intercept	0.517***	-0.066	0.464***	0.467***
	(0.010)	(0.237)	(0.053)	(0.057)
County Fixed effects?	No	Yes	Yes	Yes
Observations	2,507	2,464	2,425	2,424
Adjusted R^2	0.024	0.346	0.332	0.332
Residual Std. Error	0.281 (df = 2505)	0.229 (df = 2116)	0.232 (df = 2412)	0.232 (df = 2410)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.5.2 Models on Affective Polarization

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 4-4. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
White Deindustrialization	929	0	0.0	0.0	0.0	0.0	0.3
Non-White Deindustrialization	919	0	0.0	0.0	0.0	0.0	0.2
Deindustrialization	929	0	0.1	0.0	0.0	0.0	0.4
Racial Resentment	20	14	0.6	0.3	0.0	0.6	1.3
Unemployment	339	0	6.6	1.6	2.6	6.4	23.5
Non-White Share	929	0	0.2	0.1	0.0	0.2	0.7
College Share	929	0	0.2	0.1	0.1	0.2	0.5
Service	929	0	0.0	0.0	0.0	0.0	0.0
Income	6	2	3.0	1.1	1.0	3.0	5.0
Age	74	0	49.9	19.0	0.0	52.0	90.0

Figure 4-5. Categorical variables

Party ID	N	%
Democrats	1135	39.0
Independents	361	12.4
Republicans	1404	48.2

Table 4-3 reports the results for the partisan affective polarization estimates. Model 1 is a baseline model with only the predictor, white manufacturing layoffs. Models 2 to 3 are the main instrumental variable models. In all three specifications, white manufacturing layoffs are negative and not statistically significant. The results indicate that hypothesis two that localized deindustrialization leads to a higher level of partisan affective polarization is not supported by the empirical evidence. Therefore, affective polarization might not be the main causal mechanism by which deindustrialization affects right-wing populism.

Table 4-3. Models on deindustrialization and partisan affective polarization

Deindustrialization and Affective Polarization

	Dependent variable:			
	Polarization			
	OLS		*instrumental variable*	
	(1)	(2)	(3)	(4)
White Deindustrialization	-38.032	-46.538	-70.648	-77.516
	(25.419)	(33.114)	(80.949)	(82.038)
Unemployment		0.250	-0.678	-0.570
		(0.381)	(1.204)	(1.276)
Percent College			-22.426	-21.040
			(29.065)	(29.867)
Non-White Percentage			19.882	18.156
			(14.720)	(15.843)
Deindustrialization Service				-143.427
				(548.961)
Income			0.244	0.248
			(0.667)	(0.667)
Female		0.464	0.243	0.234
		(1.237)	(1.332)	(1.333)
High School		-1.077	-0.696	-0.697
		(1.699)	(1.910)	(1.910)
Some College		-8.215	-8.396	-8.417
		(8.048)	(8.807)	(8.810)
College and above		-0.796	-0.399	-0.413
		(1.420)	(1.569)	(1.571)
Independent		-1.543	-1.414	-1.412
		(1.251)	(1.400)	(1.400)
Republican		0.160^{***}	0.191^{***}	0.191^{***}
		(0.033)	(0.036)	(0.036)
Age	40.317^{***}	32.055^{***}	24.203	25.037
	(1.053)	(3.362)	(20.328)	(20.441)
County Fixed effects?	No	Yes	Yes	Yes
Observations	2,539	2,505	2,456	2,456
Adjusted R^2	0.0005	0.008	0.029	0.028
Residual Std. Error	30.867 (df = 2537)	30.749 (df = 2496)	30.355 (df = 2109)	30.364 (df = 2108)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.5.3 Models on Liberal Policies

Here is the descriptive statistics for all the variables used in the models in this part:

Figure 4-6. Continuous variables

	Unique	Missing Pct.	Mean	SD	Min	Median	Max
White Deindustrialization	2167	0	0.0	0.0	0.0	0.0	0.3
Non-white Deindustrialization	2127	0	0.0	0.0	0.0	0.0	0.7
All Deindustrialization	2168	0	0.0	0.0	0.0	0.0	0.9
Minimum Wage	3	0	0.7	0.5	0.0	1.0	1.0
Welfare	3	44	0.3	0.5	0.0	0.0	1.0
Healthcare	3	41	0.8	0.4	0.0	1.0	1.0
Education	3	38	0.9	0.4	0.0	1.0	1.0
Conservative Racial Attitudes	14	13	0.3	0.2	0.0	0.3	1.0
Age	75	0	47.6	16.9	18.0	47.0	94.0
Unemployment	2175	0	74.9	47.7	−78.4	74.2	358.6
Foreign born change	2145	0	55.7	55.0	−100.0	42.3	1100.0
Female	2	0	0.5	0.5	0.0	1.0	1.0
Latino Percentage Change 00-14	2152	0	97.3	67.9	−100.0	84.0	1684.0
Family Econ Worse	6	0	0.5	0.3	0.0	0.5	1.0
Relative Deprivation	3	10	0.6	0.5	0.0	1.0	1.0
Manufacturing job change 00-14	2175	0	−26.2	11.8	−81.3	−27.4	216.0
Anti-immigration	5	0	0.5	0.4	0.0	0.5	1.0
Union Member	4	0	1.5	0.7	1.0	1.0	3.0
Conservative Ideology	5	0	3.1	1.1	1.0	3.0	5.0
College	2	0	0.4	0.5	0.0	0.0	1.0
South	2	0	0.3	0.4	0.0	0.0	1.0
Family Income	13	10	6.4	3.2	1.0	6.0	12.0
Unemployed	2	0	0.0	0.2	0.0	0.0	1.0

Figure 4-7. Categorical variables

Party ID	N	%
Democrat	13846	32.0
Independent	16933	39.1
Republican	12528	28.9

Table 4-5 shows the results of the IV models on support for liberal policies. In the four full models, the coefficients on minimum wage and welfare are negative and significant. The coefficient on support for healthcare is negative but not statistically significant, although the p-value is close to the 0.1 significance level. In the baseline model in which I only include the predictor on healthcare, the predictor, of white manufacturing layoffs is negative and significant on a 0.05 level. The coefficient of the white manufacturing layoffs on support for education spending is positive but not significant. These results provide partial support for the third hypothesis that in counties where deindustrialization is high, white workers are less likely to support liberal policies on redistribution. It is worth noting that, in these models, I include a bunch of other individual-level economic factors like if a worker is unemployed, the feeling of relative deprivation. More importantly, I also include racial attitudes and anti-immigration attitudes. The two attitudes are all negative and significant in all four models. Which indicates that white identity backlash is real. The effects of white manufacturing layoffs on the probability of support for minimum wage and welfare spending are nontrivial. One unit increase in white manufacturing layoffs in a county would increase the workers' probability of not supporting minimum wage by 29%. One unit increase in white manufacturing layoffs in a county would decrease the workers' probability of supporting government spending on welfare by 76.9%. The main predictor is not significant in the healthcare model, it can be interpreted as healthcare is different and directly related to one's health. The effect of white manufacturing layoffs on public spending on education is positive and can be interpreted as that education is a non-traditional form of redistribution. Most white people generally agree it's a good thing, even the non-whites can benefit from this. The mixed results are consistent with previous literature. When examining policies on redistribution, it is worthwhile to differentiate the policies, not all liberal policies are the same. Voters do not necessarily view these policies as a bundle (Iversen & Goplerud, 2018)

Table 4-4. OLS models on public support for liberal policies

White Deindustrialization and Support for Liberal Policies

	Dependent variable:			
	minimum_wage	welfare	healthcare	edu
	(1)	(2)	(3)	(4)
White Deindustrialization	-0.342***	-0.408***	-0.133	0.169*
	(0.104)	(0.119)	(0.111)	(0.097)
Racial Attitudes	-0.388***	-0.400***	-0.447***	-0.373***
	(0.013)	(0.015)	(0.014)	(0.012)
Anti-immigration	-0.146***	-0.247***	-0.089***	-0.082***
	(0.009)	(0.010)	(0.009)	(0.008)
Non-White Share	0.066***	0.112***	0.023	0.050**
	(0.021)	(0.024)	(0.022)	(0.019)
Unemployment	0.003*	-0.005***	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Family Econ Worse	-0.047***	-0.092***	-0.049***	-0.100***
	(0.010)	(0.011)	(0.010)	(0.009)
Relative Deprivation	0.011	-0.033***	-0.013	-0.044***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Income	-0.009***	-0.023***	-0.017***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)
Unemployed	0.060***	0.096***	0.020	0.002
	(0.013)	(0.015)	(0.013)	(0.012)
Foreign-born Change (00-14)	-0.0001*	-0.0001	-0.00003	0.0001***
	(0.00004)	(0.00005)	(0.00004)	(0.00004)
Union Member	0.020***	0.003	0.007**	0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Female	0.018***	-0.058***	0.031***	0.051***
	(0.005)	(0.005)	(0.005)	(0.004)
College	-0.081***	0.043***	-0.063***	-0.040***
	(0.005)	(0.006)	(0.006)	(0.005)
Party ID	-0.330***	-0.336***	-0.269***	-0.087***
	(0.006)	(0.007)	(0.007)	(0.006)
Age	0.0002	-0.0004***	0.0002*	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Intercept	1.047***	1.099***	1.183***	1.160***
	(0.022)	(0.025)	(0.023)	(0.020)
County Fixed effects?	No	No	No	No
Observations	27,594	17,873	18,886	19,936
Adjusted R^2	0.341	0.467	0.355	0.207
Residual Std. Error	0.386 (df = 27578)	0.352 (df = 17857)	0.332 (df = 18870)	0.300 (df = 19920)
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 4-5. Instrumental variable models on public support for liberal policies

White Deindustrialization and Support for Liberal Policies

	Dependent variable:			
	minimum_wage	welfare	healthcare	edu
	(1)	(2)	(3)	(4)
White Deindustrialization	-0.290**	-0.769***	-0.118	0.155
	(0.137)	(0.156)	(0.147)	(0.128)
Racial Attitudes	-0.388***	-0.400***	-0.447***	-0.373***
	(0.013)	(0.015)	(0.014)	(0.012)
Anti-immigration	-0.146***	-0.246***	-0.089***	-0.082***
	(0.009)	(0.010)	(0.009)	(0.008)
Non-White Share	0.071***	0.078***	0.025	0.048**
	(0.023)	(0.026)	(0.024)	(0.021)
Unemployment	0.003*	-0.004**	0.001	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)
Family Econ Worse	-0.047***	-0.093***	-0.049***	-0.101***
	(0.010)	(0.011)	(0.010)	(0.009)
Relative Deprivation	0.011	-0.035***	-0.013	-0.044***
	(0.008)	(0.009)	(0.008)	(0.007)
Family Income	-0.008***	-0.024***	-0.017***	-0.010***
	(0.001)	(0.002)	(0.001)	(0.001)
Unemployed	0.060***	0.095***	0.020	0.002
	(0.013)	(0.015)	(0.013)	(0.012)
Foreign-born Change (00-14)	-0.0001*	-0.0001	-0.00003	0.0001***
	(0.00004)	(0.00005)	(0.00004)	(0.00004)
Union Member	0.020***	0.003	0.007**	0.002
	(0.003)	(0.004)	(0.003)	(0.003)
Female	0.018***	-0.057***	0.031***	0.052***
	(0.005)	(0.005)	(0.005)	(0.004)
College	-0.081***	0.042***	-0.063***	-0.040***
	(0.005)	(0.006)	(0.006)	(0.005)
Party ID	-0.330***	-0.336***	-0.269***	-0.087***
	(0.006)	(0.007)	(0.007)	(0.006)
Age	0.0002	-0.0004***	0.0002*	-0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Intercept	1.044***	1.118***	1.182***	1.161***
	(0.022)	(0.025)	(0.023)	(0.020)
County Fixed effects?	Yes	Yes	Yes	Yes
Observations	27,594	17,873	18,886	19,936
Adjusted R^2	0.341	0.466	0.355	0.207
Residual Std. Error	0.386 (df = 27578)	0.352 (df = 17857)	0.332 (df = 18870)	0.300 (df = 19920)
Note:				*p<0.1; **p<0.05; ***p<0.01

4.6 Robustness Checks

For the model on racial resentment, I conducted three robustness checks. First, I replace the main predictor–white manufacturing layoffs with all manufacturing layoffs. "All manufacturing layoffs" includes non-white manufacturing layoffs in counties. It reflects the general trend of manufacturing situations in different counties (table 4-6). Second, I expand the ANES dataset to include previous years. In this case, I include the 2012 ANES survey with the same set of variables (table 4-7). Third, I fit models by only including county-level control and individual-level characteristics respectively (table 4-8). In all these models, manufacturing layoffs are positive and statistically significant.

Table 4-6. All deindustrialization and racial resentment

All deindustrialization and racial resentment

	Dependent variable:		
	Resentment		
	(1)	(2)	(3)
All Deindustrialization	1.201***	0.670***	0.685***
	(0.189)	(0.240)	(0.250)
Unemployment	0.001	-0.007*	-0.007*
	(0.003)	(0.003)	(0.004)
Percent College		-0.456***	-0.458***
		(0.102)	(0.102)
Non-White Percentage		-0.027	-0.024
		(0.042)	(0.044)
Deindustrialization Service			0.533
			(2.880)
Income		-0.013***	-0.013***
		(0.005)	(0.005)
Female	0.002	-0.001	-0.001
	(0.010)	(0.010)	(0.010)
High School	0.140***	0.120***	0.120***
	(0.013)	(0.013)	(0.013)
Some College	0.117	0.087	0.085
	(0.071)	(0.071)	(0.075)
College and above	0.112***	0.098***	0.098***
	(0.011)	(0.011)	(0.011)
Independent	0.194***	0.185***	0.185***
	(0.016)	(0.016)	(0.016)
Republican	0.286***	0.282***	0.282***
	(0.010)	(0.010)	(0.010)
Age	0.001***	0.001***	0.001***
	(0.0003)	(0.0003)	(0.0003)
Intercept	0.236***	0.471***	0.466***
	(0.025)	(0.051)	(0.057)
County Fixed effects?	No	No	No
Observations	2,464	2,425	2,424
Adjusted R^2	0.314	0.330	0.330
Residual Std. Error	0.234 (df = 2454)	0.232 (df = 2412)	0.232 (df = 2410)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4-7. Models on both 2012 and 2016

Deindustrialization and Racial Resentment 2012, 2016			
	Dependent variable:		
	Resentment		
	(1)	(2)	(3)
All Deindustrialization	0.323**	0.240**	0.226**
	(0.139)	(0.100)	(0.090)
Unemployment	-0.052***	-0.076***	-0.077***
	(0.008)	(0.006)	(0.007)
Percent College	0.004	-0.004***	-0.005***
	(0.003)	(0.001)	(0.002)
Non-White Percentage		-0.323***	-0.329***
		(0.049)	(0.059)
Deindustrialization Service			1.592
			(1.570)
Income		0.005**	0.005*
		(0.002)	(0.002)
Female	-0.003	-0.004	-0.004
	(0.005)	(0.005)	(0.005)
High School	0.104***	0.112***	0.112***
	(0.007)	(0.007)	(0.007)
Some College	0.115***	0.121***	0.119***
	(0.021)	(0.021)	(0.021)
College and above	0.091***	0.094***	0.093***
	(0.006)	(0.006)	(0.006)
Independent	0.133***	0.145***	0.142***
	(0.008)	(0.008)	(0.008)
Republican	0.248***	0.257***	0.255***
	(0.006)	(0.006)	(0.006)
Age	0.0005***	0.001***	0.001***
	(0.0001)	(0.0001)	(0.0001)
Intercept	0.263***	0.485***	0.482***
	(0.051)	(0.025)	(0.042)
County Fixed effects?	No	Yes	Yes
Year Fixed Effects?	Yes	Yes	Yes
Observations	8,523	8,332	8,331
Adjusted R^2	0.273	0.259	0.263
Residual Std. Error	0.230 (df = 8118)	0.232 (df = 8319)	0.232 (df = 8269)
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 4-8. Models with only individual/county level controls

Deindustrialization and Racial resentment only Individual/County Controls

	Dependent variable:	
	Resentment	
	(1)	(2)
All Deindustrialization	1.199^{***}	0.709^{**}
	(0.190)	(0.294)
Unemployment	0.002	
	(0.010)	
Percent College	0.140^{***}	
	(0.013)	
Non-White Percentage	0.117	
	(0.071)	
Deindustrialization Service	0.112^{***}	
	(0.011)	
Income	0.194^{***}	
	(0.016)	
Female	0.286^{***}	
	(0.010)	
High School	0.001^{***}	
	(0.0003)	
Some College		-0.013^{***}
		(0.004)
College and above		-0.947^{***}
		(0.118)
Independent		-0.047
		(0.052)
Republican		2.418
		(3.398)
Age		-0.020^{***}
		(0.005)
Intercept	0.242^{***}	0.896^{***}
	(0.018)	(0.062)
County Fixed effects?	No	No
Observations	2,464	2,466
Adjusted R^2	0.315	0.070
Residual Std. Error	0.234 (df = 2455)	0.275 (df = 2459)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$	

4.7 Conclusion

In this chapter, I empirically test the causal mechanism by which deindustrialization affects right-wing populism. I mainly focus on negative identity politics and related attitudes toward liberal policies. The results show that while partisan affective polarization is not a mechanism by which deindustrialization affects right-wing populism, racial resentment is. Relatedly, public views on some liberal policies on redistribution might also work as mechanisms. Racial attitudes significantly affect the probability of supporting liberal policies. Furthermore, not all liberal policies are the same, when examining the effects of deindustrialization on these policies, we should examine them separately. Furthermore, instead of examining the individual effects of trade shock and automation shock, I examine the combined effects of the two. In the previous two chapters, trade shock and automation shock do not have independent effects on partisan affective polarization and racial attitudes. The results in this chapter show that the combined effects are meaningful for negative identity politics in the US.

CHAPTER 5: CONCLUSION

In this dissertation, I ask two important research questions that examine the structural reasons of contemporary U.S. politics, which are increasingly characterized by negative identity politics—specifically, pronounced partisan polarization and deepening racial divisions. The questions are: What drives the manifestation of negative identity politics in today's U.S. political landscape? And how do structural economic shifts influence the emergence of right-wing populism? To address these questions, I have constructed a theoretical framework positing that structural economic transformations, with a significant emphasis on deindustrialization, play a crucial role in fueling the ascendance of negative identity politics within the United States. This framework challenges the prevailing narratives that attribute the rise of individual-level negative identity backlashes primarily to trade shocks from China and automation. Instead, I argue that the core mechanisms through which structural economic factors catalyze right-wing populism are predominantly through racial backlash among white populations. This analysis reveals that partisan polarization and grievances related to redistributive policies do not serve as the principal channels through which economic downturns facilitate the surge of right-wing populism. Rather, the study underscores the importance of understanding racial dynamics and their interplay with economic variables in explaining the reactionary stance of white populations against the backdrop of structural economic shocks.

At the heart of my study is an in-depth exploration of the interconnections between the political economy of identity politics, specifically aiming to illuminate the core causal mechanisms driving the political economy of right-wing populism within a Western context. This research joins the debates on whether it is primarily cultural or economic disruptions that ignite such political backlash. The analysis reveals that this is not merely a question of choosing between cultural or economic factors; rather, it is an interplay where cultural backlash manifests as a mis-perceived response of certain social identity groups to structural economic changes. This stands in contrast to the prevailing discourse within current literature, which predominantly investigates the broad, aggregate-level impacts of trade and automation shocks on the rise of right-wing populism in the United States. Diverging from this approach, my focus narrows down to the individual level, seeking to unravel the micro-foundations of right-wing backlash. This involves a detailed examination of the individual responses to the long-term economic disturbances caused by trade, automation, and deindustrialization. Through this lens, the study aims to provide a nuanced understanding of the intricate ways in which economic changes influence personal identity and political alignment, challenging existing narratives and highlighting the complexity of individual reactions to macroeconomic trends.

Empirically, my research undertakes a rigorous examination of the impacts of trade shock, automation shock, and deindustrialization at large on the manifestations of negative white identity politics. This encompasses aspects such as partisan affective polarization, symbolic racialism, and the stance of the public on liberal redistributive policies within the United States. My findings reveal a notable absence of micro-level evidence to substantiate the role of either trade or automation shocks as sole contributors to the identity backlash observed among American white voters. Instead, it finds that the more immediate, encompassing, and tangible effects of local-level manufacturing job losses, along with the resultant adverse impacts on local economies and communities, provide a more accurate explanation for these identity-driven backlashes. This indicates that voters exhibit a heightened responsiveness to the direct repercussions of economic downturns, like manufacturing layoffs, over the more abstract influences posed by trade and automation. Additionally, in a departure from prevalent assumptions, it also finds that in regions severely affected by economic shocks, white populations do not exhibit a heightened demand for redistribution, instead, they ask for less redistribution in certain issue areas. The dynamics of identity politics significantly influence the policy orientations of white workers, presenting a challenge to conventional models of economic voting within the political economy. This nuanced understanding underscores the complexity of voter behavior, suggesting that identity politics and economic decline interlace to shape political stances in ways that traditional economic voting models may not fully capture.

This research significantly advances our understanding of the intricate dynamics between structural economic declines and cultural disturbances, highlighting the need to conceptualize deindustrialization as a broad phenomenon rather than isolating specific instances of local labor market upheavals. The prevailing discourse surrounding the backlash against globalization and automation tends to overstate the significance of these discrete events, attributing to them an outsized role in shaping societal and political responses. In contrast, this study advocates for a broader perspective that recognizes the cumulative impact of general local manufacturing job disruptions, moving beyond the narrow focus on trade or automation as solitary sources of deindustrialization. Moreover, this investigation brings to the forefront the critical role that racial divisions play in mediating the transition from economic adversity, for instance deindustrialization, to the emergence of negative political dynamics within the American landscape. By doing so, it calls into question the foundational assumptions underlying the existing literature on trade shock and automation's influence on right-wing populism, proposing an innovative theoretical framework and methodological approach. This framework offers a novel lens through which to examine the local-level economic disruptions and their consequent identity-based reactions, providing fresh insights into the mechanics of how economic shocks are translated into political and social division. In essence, the study not only challenges the micro-foundations of prevailing narratives on economic shock and political reaction but also sets forth a new theory and a refined measurement strategy. It underscores the necessity of adopting a multifaceted and integrative approach to understanding the socio-political ramifications of deindustrialization.

From these findings, it is evident that policy responses to political backlash in the U.S. today, while needing to consider the macro-level negative impacts of trade and technological change, should also concentrate on the specificities of local communities. Policies must be crafted to address localized issues directly. Additionally, when considering the white backlash, policymakers should divert their attention from party politics to strategies that can mitigate racial bias. Adopting strategies like the Contact Hypothesis, which promotes increased interaction among diverse groups to reduce prejudice, could offer a forward path. Policies fostering community diversity and combating segregation, coupled with educational and labor market initiatives that aim at inclusivity and economic stability, could significantly contribute to mitigating the roots of political and racial discord, weaving a stronger societal fabric. Integral to this approach are policies aimed at cultivating community diversity and dismantling segregation barriers. Adding to this, educational initiatives that facilitate the re-education of workers for integration into non-manufacturing sectors are crucial. Such policies should transcend the narrow focus on trade and automation, recognizing the potential for trade discussions to be exploited by political entrepreneurs who may fan the flames of anti-foreign and anti-minority sentiment, leading to damaging protectionist measures. Instead, a holistic strategy that includes re-skilling and up-skilling programs, aimed at bolstering economic stability and inclusivity, could play a pivotal role in addressing the underlying causes of political and racial strife, fostering a more unified and resilient societal structure.

However, it should be noted that the interplay between economic shocks and identity politics is a very complex issue. While deindustrialization serves as a significant backdrop, potentially acting as a root cause, it should not be viewed as the sole or direct instigator of identity-driven backlashes. Instead, deindustrialization represents a necessary but not always sufficient condition for such phenomena. The transition from an identity crisis to tangible actions, such as voting for unconventional political candidates, suggests that a confluence of immediate factors, beyond the broad scope of economic downturns, must be taken into account. These factors might include, but are not limited to, prevailing misperceptions among the dominant white population in the U.S., which are themselves influenced by a variety of other elements. Identity crisis sometimes is a misperception of the dominant white people. Furthermore, it is essential to recognize that local conditions can significantly mitigate the impacts of economic shocks, preventing the straightforward translation of economic distress into identity-based resentment.

The methodology employed in this research, while comprehensive, does encounter certain limitations as well. A notable constraint is the approach to symbolic racism, which is focused exclusively on the experiences of Black people in the U.S., thereby overlooking the nuanced experiences of other minority groups. This focus could potentially narrow the scope of findings, given the rich elements of racial dynamics that exists across various communities. Additionally, the study's reliance on the feeling thermometer to gauge affective polarization introduces a degree of subjectivity, as this measure can be considered somewhat arbitrary and may not fully capture the complexity of individuals' political sentiments. The use of survey data presents another set of challenges, chiefly concerning representativeness. The data may not accurately reflect the diverse perspectives and conditions across all local areas under study, leading to potential gaps in the research's geographic and demographic coverage. Furthermore, the study does not thoroughly address the issue of weighting, which is crucial for ensuring that the survey data accurately represents the broader population. Such limitations are inherent in survey data and observational studies.

The question of generalizability raises important considerations. Whether we can apply this study's findings beyond the U.S. context to other developed countries. The unique historical backdrop of slavery in the U.S. suggests that the interplay between economic shocks and negative identity politics, particularly as it pertains to racial tensions, might manifest differently in this country compared to other developed democracies with distinct historical narratives. This specificity prompts a critical examination of whether the dynamics identified in this research are uniquely American or if they echo broader patterns observable in other OECD countries, where the history and impact of slavery might not play a central role.

This study paves the way for future research inquiries. Firstly, expanding the analysis of symbolic racism to encompass a wider range of minority experiences could offer a more nuanced understanding of how racial dynamics intersect with political behaviors across different communities. This approach would enrich our comprehension of the multifaceted nature of identity politics. Additionally, enhancing the methodological rigor of studies on affective polarization through the adoption of more diverse and nuanced measurement tools could provide deeper insights into the complex landscape of political sentiments. Secondly, future studies should strive for greater representativeness in survey data, potentially through mixed-methods research that combines qualitative and quantitative analyses. This could help in addressing the challenge of establishing causality between economic shocks, identity politics, and racial dynamics. Exploring cross-national generalizability is also critical, as it would illuminate whether the phenomena observed in the U.S. resonate or diverge in different democratic contexts. There is an emerging body of research on affective polarization across nations, suggesting that the phenomena of economic shocks potentially leading to partisan identity backlashes, along with the influence of identity politics on policy, worth further exploration on an international scale. Such comparative analyses could shed light on whether factors like partisan polarization, racial tensions, and policy grievances significantly influence the dynamics of the political economy of right-wing populism in developed democracies. It might help to dissect the distinct impacts of national histories and cultural contexts on the interplay between economic adversity and political responses as well.

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