WHAT CREATES HATE?: EXAMINING THE MOTIVATIONS OF RIGHT-WING HATE GROUPS IN 2017

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ABSTRACT

Hate groups saw accelerated growth in 2017, with the size of the hate group community growing to a level not seen in recent memory. In addition to purely numbers-based growth, the composition of hate groups in the United States has shifted to be more reflective of modern grievances. Despite this growth, little research has been done to determine what environmental triggers may have facilitated the (re)activation of hate groups in the United States. Disagreement exists regarding what factors motivate hate group activity; however, a body of literature points to anxiety as being a possible culprit. Feelings of anxiety, it has been argued, may push individuals to blame others for their circumstances, creating animosity toward outgroups. Choosing to participate in a hate group has been viewed as an extension of that behavior. This thesis investigates whether that story holds merit, examining whether environmental factors were more prominent in counties that saw a newly (re)activated right-wing hate group in 2017. Specifically, this thesis uses nearest neighbor and Kernel matching to determine whether counties that saw newly (re)activated right-wing hate groups in 2017 had higher levels of economic, social, and cultural anxiety compared to those that did not. The results indicate that social and cultural anxiety were significantly higher in counties that saw newly (re)activated right-wing hate groups in 2017, but economic anxiety was not significantly more present. These findings indicate that the far-right may be shifting ideologically away from economic appeals and towards appeals that
maximize social and cultural fear. Moreover, these findings reiterate the need for authoritative research on right-wing extremism and hate groups.
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INTRODUCTION

On August 11, 2017, white nationalism staged its public rebirth. Entering the campus of the University of Virginia in protest of the removal of a Confederate statue, a legion of white men snaked through the usually quiet town of Charlottesville, armed with tiki torches and shouting chants, such as “Jews will not replace us.” The evening torchlight parade marked the beginning of a chaotic 24-hour period that would continue with a march through the city the next day. By the time the chaos quieted, three would be dead, 35 would be injured, and millions of Americans would be shocked out of their ignorance.¹

As one of the largest gatherings of the radical right in more than a decade, the spectacle, known as the Unite the Right rally, served as a reminder that the United States was far from being a post-racial society. But it also served as a reminder that the United States was far from being prepared to tackle a resurgence of the radical right.

For the past two decades, United States counterterrorism has focused almost exclusively on American and foreign-born jihadists, relegating right-wing extremism to the sidelines.² In 2008 and 2009 fewer than 350 agents in the F.B.I.’s 2,000 agent counterterrorism unit were assigned to monitor domestic terrorism. While figures for subsequent years have not been publicly released, an April 2019 report from the Daily Beast revealed that the Department of Homeland Security “[has] disbanded a group of intelligence analysts who focused on domestic

terrorism.” Furthermore, reports revealed that “the number of analytic reports produced by DHS about domestic terrorism, including the threat from white supremacists, has dropped significantly.”

In contrast, the number of right-wing extremist attacks has grown. Right-wing terrorist attacks as a proportion of all terrorist attacks grew from six percent in the 2000s to 35 percent from 2010 to 2019. Moreover, between 2008 and 2017, right-wing extremists committed 71 percent of extremist-related fatalities in the United States. In 2018, every extremist killing in the United States had a link to right-wing extremism.

But alarming signs of growth have also come from the organizational representations of the radical right: hate groups. The Southern Poverty Law Center defines a hate group as “an organization that – based on its official statements or principles, the statements of its leaders, or its activities – has beliefs or practices that attack or malign an entire class of people, typically for their immutable characteristics.” An active hate group is defined as a hate group that performs at least one “action” (rally, protest, etc.) in a given year. In the past half century, hate groups have largely existed in the fringes of American society; but data suggests this may no longer be the case.

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4 Woodruff, "Exclusive: Homeland Security Disbands Domestic Terror Intelligence Unit."
In fact, hate groups have seen rapid growth over the past five years. By the end of 2017, the United States was home to 954 active hate groups, up 4 percent from 2016 and 20 percent from 2014.⁹ In 2017, those 954 hate groups could also be found in all 50 states, the first time that has been true since 2009.¹⁰

In many ways, 2017 was a continuation of an already documented pattern of hate group growth. But 2017 was also a divergence point, in which new trends emerged. Most significantly, the composition of the hate group landscape shifted, as the radical right began to modernize itself. Responding to tectonic cultural and political divides, anti-Muslim and anti-immigrant groups saw punctuated growth, attracting more membership from increasingly radicalized Americans.¹¹ The Ku Klux Klan, on the other hand, saw a dramatic decline in chapters, as white nationalists abandoned white hoods for membership in the alt-right.¹² Hate groups also increasingly turned to social media and digital message boards to recruit new members and expand their sphere of influence.

A historic divergence in the public’s view of right-wing extremism also seemed to occur in 2017. Following the United the Right rally in Charlottesville, an ABC News/Washington Post poll found that approximately 22 million Americans deemed it “acceptable” to hold neo-Nazi or

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white supremacist views. And some have argued that one of those 22 million Americans may be the president of the United States.

Beginning with the inauguration of Donald J. Trump, 2017 marked a year that energized those in the radical right. With support from white supremacist organizations like the Ku Klux Klan, and a reluctance to condemn white nationalist activities, Trump was perceived by many in the radical right to be an ally in the White House. Hate groups championing right-wing discriminatory ideals became emboldened by a president that, they believed, shared many of their views.

The tension between the growth of right-wing extremism and the seeming apathy of the government is worth investigating. The reality is that the threat of right-wing extremism is growing rapidly both at home and abroad. In the six months prior to this writing, Americans have been forced to grapple with pipe bombs sent to liberal politicians and media organizations, a mass shooting at the Tree of Life synagogue in Pittsburg, and the arrest of a member of the Coast Guard planning mass politically-motivated violence, all of which suggest right-wing domestic threats should be taken seriously. The killings of 49 Muslims in New Zealand at the

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13 Reitman, "U.S. Law Enforcement Failed to See the Threat of White Nationalism. Now They Don't Know How to Stop It."
hands of a man radicalized by right-wing extremists only add to that sense of urgency. Yet at the same time, Donald Trump continues to maintain that right-wing extremists are “…a small group of people…”

Mitigating the rise of right-wing extremists principally starts with understanding why such a rise is happening. But given the United States government has taken little public action to understand the motivations of right-wing extremists, this study will attempt to fill in some of those research gaps. To do so, this thesis will examine the radical right’s organizational arm by analyzing right-wing hate groups that became newly (re)activated in 2017 to determine what factors may have influenced the radicalization and (re)activation of right-wing extremists. Specifically, this thesis will use nearest neighbor and Kernel matching to question whether county-level markers of cultural, social, and economic anxiety were significantly higher in counties that saw newly (re)activated right-wing hate groups in 2017, referred to as “NAHG counties.”

After the Oklahoma City Bombing on April 19, 1995, by right-wing extremist, Timothy McVeigh, the United States government began recognizing right-wing extremism as a domestic threat. In doing so, an array of resources was built to gather intelligence and monitor the far-right. Almost a quarter of a century later, the problem persists, but the infrastructure has eroded. In the face of increasing threats from the far-right, now seems as good a time as any to rebuild.

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LITERATURE REVIEW

A significant body of research has been devoted to studying extremism and radicalization; however, researchers have struggled to reach a consensus on how extremist organizations are able to broaden their appeal and membership base. Most of the resulting literature examines the recruitment process, with a specific focus on how extremists, both international and domestic, frame their messages to attract new members. However, some research has also been conducted to understand how environmental factors can contribute to the creation of extremist groups, particularly regarding hate groups in the United States.

The Link Between Anxiety and Extremism

There is strong psychological evidence that suggests anxiety plays a crucial role in pushing individuals towards extremism. McGregor, Nash, Mann, and Phillis (2010) examine the link between anxiety and reactive approach motivation (RAM), a behavioral response that causes psychological tunnel vision and avoids feelings of discomfort. The conclusion of four different experiments that controlled for levels of anxiety indicates psychological and biological evidence of RAM is present when individuals are placed in environments that cause them to feel heightened stress and uncertainty.

McGregor, Nash, and Prentice (2010) expand on this finding, by extending the link between RAM and religious extremism. Positing that the psychological tunnel vision created by RAM can be weaponized to cause individuals to embrace extreme religious ideals, the authors conducted three different studies on religious zeal. The results indicate that there is sufficient evidence to suggest RAM can lead individuals to move towards religious extremes. Taken together, these two studies suggest that there is an observable relationship between anxiety and
religious extremism. While domestic hate groups do not exclusively engage in religious extremism, understanding that anxiety can be a tool to radicalize individuals towards a cause is important to understanding the triggers that might lead individuals to embrace extremism.

**Radicalization and Recruitment of Extremists Abroad**

Most of the literature examining radicalization and recruitment of extremist groups examines extremism in an international context, whether studying terror networks or groups in the global radical right. Doosje, Loseman, and Van Den Bos (2013) examine the factors that contribute to the radicalization of Islamic youth in the Netherlands. Using an online questionnaire completed by 131 non-radicalized, 13 to 21-year-old Islamic Netherlanders, the motivations of radicalization were closely scrutinized. The results indicate that factors such as individual social deprivation, a perceived group threat, and perceptions of injustice are prominent determinants of radicalization. The study also found that individuals most susceptible to radicalization experience heightened anxiety while interacting with individuals they perceived as different.

Lucassen and Lubbers (2012) analyze right-wing preferences in European elections to determine what leads individuals to align themselves with the radical right. Using the first round of data from the European Social Survey, an individual’s right-wing preference was examined alongside socioeconomic and demographic characteristics, the presence of economic and cultural threats (unemployment, immigration, etc.), and the characteristics of the country they reside. The analysis reveals the perception of economic and cultural threats has a significant impact on an individual’s right-wing voting preferences, with the anxiety regarding cultural threats having a larger impact than anxiety regarding economic threats. While substantial differences exist
between domestic hate groups and international extremists, understanding how international groups attract new members can provide a window into the messaging frames that domestic extremist groups might also use.

**Hate Group Recruitment via Anxiety**

Research regarding the recruitment methods of domestic hate groups, and in particular white extremists, has found common messaging frames revolving around fear, perceived victimhood, and anxiety. Adams and Roscigno (2005) examine the recruitment tactics that white supremacist groups use online. Using an automated linguistic analysis, symbolic frames were established based on the content of white supremacist activity on the internet. For a group like the Ku Klux Klan, the analysis finds that messaging was focused on broadcasting the perceived injustices faced by white people with the blame being placed on non-white actors. Neo-Nazi messaging was similar; however, instead of blaming non-white actors, Neo-Nazis made multiculturalism the culprit. Regardless of who or what these groups blamed, online activity by white supremacists reveals their common use of anxiety-laden messaging to draw new recruits into the fold.

Blazak (2001) analyzes what types of individuals Nazi skinheads typically target for recruitment. Of particular focus is strain theory, or the belief that those who experience negative stimuli, perceive blocked opportunities, or wrestle with feelings of rootlessness are most susceptible to radicalization. Interviews from Blazak (1995), a seven-year ethnographic study, were used to determine which populations were targets for Nazi skinhead recruitment. Examination of the data finds that skinheads typically emphasized four different kinds of threats when recruiting new members: threats to racial status, gender status, heterosexual status, and
economic status. Given this fear-laced messaging, skinhead recruitment typically targeted white youth that felt isolated or displaced, allowing skinheads to cast themselves as friends who could provide help. By targeting the socially disconnected, skinheads maximized the effectiveness of their anxiety-based communication.

**Hate Group Recruitment via Other Means**

Still, other studies suggest hate group recruitment, particularly recruitment in white supremacist organizations, is motivated by factors unrelated to feelings of anxiety. Browman-Grieve (2009) examines the content that is posted in the white supremacist virtual community, Stormfront. Virtual communities allow for discourse to develop and propaganda to be distributed. They can also act as windows into community dynamics. The authors examined Stormfront’s content using a Thematic Content Analysis. The findings suggest that while fear-based and hate-based messaging existed in white supremacist virtual communities, it was feelings of social belonging that kept members actively engaged. These social connections also influenced recruitment, as Stormfront visitors typically brought friends and family into the community, rather than strangers radicalized by an ideology. Instead of recruitment being prompted by anxiety, the findings suggest that recruitment may be more closely influenced by personal connections and networking.

Gerstenfeld, Grant, and Chiang (2003) analyze content posted in 157 extremist websites to determine what types of content existed on each. The websites represented views ranging from White Nationalists to Holocaust Deniers. The findings conclude there was no consistent type of content or messaging that appeared in all extremist sites. While economic issues appeared on a majority of the sites, that majority only accounted for 50.3 percent of the sample. Meanwhile,
49.7 percent of the websites contained racist iconography, while 21.7 percent of them denied being racist. Although the recruitment potential of these websites was strongly acknowledged, the inconsistent messaging raises questions as to whether there is a universal theme present in the external messaging of hate groups.

The Geography of Hate

Prior research has attempted to perform analyses similar to the one this study is attempting to conduct by examining what factors can predict the presence of hate groups. Durso and Jacobs (2013) examine what determinants can predict the number of white supremacist groups on a state level by analyzing the Southern Poverty Law Center’s annual record of hate groups, United States Census and American Community Survey data, as well as data from the Department of Justice’s Uniform Crime Report. The findings indicate variables like unemployment, the murder rate, and the percentage of black residents all significantly affected the presence of white supremacist groups. This implies that proxies for economic anxiety (unemployment), social anxiety (the murder rate), and cultural anxiety (the percentage of black residents) influenced the creation of hate groups throughout the United States on a state level.

Medina, Nicolosi, Brewer, and Linke (2018) perform a county-level analysis of the factors that predict the creation of hate groups regionally using the Southern Poverty Law Center’s annual hate group data, American Community Survey data, data from the Religion Data Archive, and the Environmental System Research Institute’s Market Potential Dataset. Analysis of that data revealed poverty rates and the percentage of white residents were positively correlated with the presence of hate groups. Conversely, levels of education and spatial mobility were negatively correlated with the presence of hate groups. Religious beliefs were positively
correlated with hate groups in the South, Midwest, and East Coast, while they were negatively correlated with the presence of hate groups in the West, Northeast, and Southeast. Additionally, Republican political affiliation was positively correlated with the presence of hate groups in the East Coast, Midwest, and the South, but had no effect in other regions. This again suggests that markers of economic anxiety (poverty rates), social anxiety (spatial mobility), and cultural anxiety (percentage of white residents) predicted the presence of hate groups in the United States on a regional level.

These two studies provide a solid foundation to examine the determinants of hate groups in the United States, but this study aims to build upon those findings. This thesis will incorporate elements of both studies. While it will use a county-level analysis like the one found in Medina, Nicolosi, Brewer, and Linke (2018), it will look outside sociodemographic characteristics for the analysis. And while it will use similar variables as Durso and Jacobs (2013) did, it will be far more robust in choosing markers that intentionally serve as proxies for anxiety. Furthermore, while both studies focus on the presence of hate groups, this study will seek to tell a different story – one regarding the (re)activation of hate groups in a specific period of time. Finally, while both studies seek to determine what factors were most predictive of the presence of hate groups, this study instead seeks to understand what factors were significantly more present in counties that saw newly (re)activated right-wing hate groups in 2017 compared to those that did not.

**CONCEPTUAL FRAMEWORK**

The exact motivations that nudge individuals down the path of radicalization and extremism are still widely debated among scholars. There is no universally accepted theory that
can explain how and why individuals choose to join extremist groups. However, there are theories that hold more legitimacy in academic spaces than others.

The conceptual framework for this thesis is adapted from the Staircase Model of Terrorism proposed by Fathali Moghaddam and is illustrated in Figure A1.\textsuperscript{21} Moghaddam principally believes that terrorism is motivated by societal-level variables, such as demographic changes or poor economic circumstances. These societal-level variables, in turn, cause psychological anxiety and uncertainty in those that feel harmed by the changes. This anxiety is then internalized, causing the individual to see themselves as the victim of societal change and to see “outgroups” as the perpetrators of it. By creating an “us” versus “them” mentality, these individuals are then gradually radicalized against the “other.” Once that radicalization passes a certain threshold, individuals are then susceptible to participating in terrorism.\textsuperscript{22}

While this thesis deals with extremism, rather than terrorism, limited research on domestic extremism means a conceptual understanding of domestic radicalization is elusive. However, because entry into both extremism and terrorism is done through radicalization, the same mechanics Moghaddam elucidates may still reasonably apply in a domestic context. It should be noted that while Moghaddam focuses on the motivations that impact individuals, this thesis is focused on the county-level. As a result, this thesis incorporates two conceptual frameworks: one illustrating an individual path to extremism, and another that is a county-level analog to the individual-level explanation. Both are illustrated in Figure A2.

Like the Staircase Model, this thesis’s conceptual framework begins by focusing on how an individual interprets societal-level change and uncertainty. On an individual level, this

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\begin{enumerate}
\item Fathali M. Moghaddam, ”The Staircase to Terrorism: A Psychological Exploration,” \textit{American Psychologist} 60, no. 2 (2005), doi:10.1037/0003-066x.60.2.161.
\item Ibid.
\end{enumerate}
\end{flushright}
uncertainty manifests in economic, social, and cultural anxiety. In this case, economic anxiety indicates some sort of economic-related distress; social anxiety indicates a negative reaction to societal changes or phenomena; and cultural anxiety indicates discomfort with the cultural atmosphere of the environment. These seek to encompass the different stressors that individuals might experience in a local context.

On the county-level, anxiety cannot be easily measured. However, there are county-level proxies that can account for these different types of anxiety. As an analog, economic anxiety can be substituted for indicators of economic decline; social anxiety can be analyzed by metrics of social turmoil; and cultural anxiety can be examined through measurements of cultural dissimilarity. For example, rather than gauging an individual’s economic anxiety, a county-level proxy of the unemployment rate could be used to determine whether an area may have a general atmosphere of economic uncertainty. Similarly, rather than gauging individual social anxiety, violent crime rates in counties can serve as a measurable indicator of social stress.

The presence of these three types of anxiety, whether examined on an individual or county level, is directly tied to feelings of victimhood. This is a natural progression. After experiencing enough negative stimuli, individuals often begin to believe themselves to be the victims of a change or policy. On an individual level, this manifests itself in the perception of victimhood, or how individuals internally frame themselves as the “losers” of a scenario. In this case, economic, social, and cultural anxiety leads individuals to view their circumstances as a product of societal change, fueling perceptions of inferiority.

It should be noted that the relationships between economic anxiety, social anxiety, cultural anxiety, and victimhood work both ways, as economic, social, and cultural anxiety can also be fueled by feelings of victimhood. This is because the continued perception of victimhood
can imbue individuals with increasing social and cultural anxiety, while also potentially
damaging their performance in the workforce, raising anxiety about their economic stability.

On the county level, an individual’s perception of victimhood is manifested in public
expressions of victimhood. Similar to victimhood at the individual-level, county-level
expressions of victimhood are fueled by economic decline, social turmoil, and cultural
dissimilarity. This is most often observed in the framing of messages and rhetoric used by those
with more privilege relative to others in society. For example, the chant “Jews will not replace
us,” used during the United the Right rally, frames white men as victims of the Jewish faith.

The relationships between expressions of victimhood, economic decline, social turmoil,
and cultural dissimilarity are similar on the county and individual-level, with each impacting the
other. This is because expressions of victimhood may signal a change in how individuals are
navigating life. This may result in economic inefficiencies throughout a county, increasingly
negative social outcomes as individuals make poorer personal decisions, and the changes in
cultural composition of a county as a result of minority-identifying individuals moving in
response to fears generated by expressions of victimhood.

After internalizing anxiety and perceiving victimhood, individuals are then incentivized
to displace the blame for their perceived problems. In psychology, this is most closely associated
with the fundamental attribution error, or the belief that negative outcomes impacting an
individual are caused by external and uncontrollable stimuli. In this scenario, individuals who
interpret themselves as victims begin to blame the “outgroup” (e.g. immigrants, racial minorities,
the poor) as the ones most responsible for their circumstances. Importantly, victimhood and

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23 Lee Ross, “The Intuitive Psychologist And His Shortcomings: Distortions in the Attribution Process,” Academic
blame shifting feed off each other, with individuals in this stage continuing to grow their insecurity and animosity together.

It is important to remember that the displacement of blame is not solely impacted by the perception of victimhood. An individual’s political leanings can influence which groups they choose to blame and to what magnitude they blame them, while an individual’s identity characteristics (e.g. race, gender, sexuality) can influence who individuals peg as the responsible party. The reverse is true as well. Blame shifting can also impact the political leanings of an individual, as antagonizing less privileged groups often moves individuals closer on the political spectrum to the far right.

On a county-level, the displacement of blame is manifested in the vilification of an outgroup. In this case, the fundamental attribution error is, again, channeled into message framing and rhetoric. For example, many in the radical right often blame rising levels of crime solely on African Americans, casting them as a violent villain in the United States, despite little evidence supporting that claim.

Like on the individual level, an individual’s politics and identity impact their vilification of an outgroup. A county’s partisanship and sociodemographic characteristics can serve as proxies for these individual-level factors. The relationships between partisanship, sociodemographic characteristics, and the vilification of an outgroup mirror the ones in the individual-level analysis.

Finally, it is the displacement of blame that leads individuals to participate in hate groups. With enough animosity towards outgroups, individuals begin looking for ways to combat those they view as a threat.²⁴ Hate groups serve as an organizational vessel for that to be

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accomplished, providing comradery and opportunities for action. Joining a hate group is certainly not the only path one might take to express that animosity, but it is a visible way in which an individual can choose to act.

However, the displacement of blame is not the only thing that leads individuals to join hate groups. Prominently, individual prejudices are also large factors that may push an individual to become involved in one. That relationship should be taken seriously and represents the principle alternative explanation for hate group participation. It should also be noted that an individual’s membership in a hate group can inflame individual prejudices and lead individuals to elevate their blame shifting.

On the county-level, the (re)activation of a hate group can serve as a proxy for membership in a hate group. These are notably different things. While membership in a hate group is an individual affair, the (re)activation of a hate group is a collective task. However, the (re)activation of a hate group is far more salient than membership in a hate group on an analytic level. Joining a hate group is a relatively straightforward task. Conversely, (re)activating a hate group is both more intentional and far more involved, requiring coordination, outreach, and the planning of an action at a minimum. Therefore, the (re)activation of a hate group may serve as a more definitive and illustrative metric.

The (re)activation of a hate group is affected by individuals’ prejudices, much like membership is. However, on the county-level, individuals’ prejudices are embodied by prejudicial behavior, such as the common usage of racially derogatory language. Similar to membership, the (re)activation of a hate group can also exacerbate prejudicial behavior and the vilification of an outgroup on a county level.
Hypotheses

Based on the referenced literature and the conceptual framework, this study proposes the following hypothesis: county-level measures of social anxiety, economic anxiety, and cultural anxiety were significantly higher in NAHG counties compared to non-NAHG counties. Additionally, this study proposes the following break-out hypotheses: (i) signs of economic decline were significantly higher in NAHG counties; (ii) perceived threats to social life were significantly higher in NAHG counties; and (iii) cultural dissimilarities were significantly higher in NAHG counties.

DATA, VARIABLES, AND METHODS

Data

This thesis uses multiple datasets to create a statistical picture of the conditions and characteristics in all United States counties. From the United States Census Bureau, this thesis incorporates data from the “Model-based Small Area Income and Poverty Estimates,” which contains measures of poverty in United States counties; the “Population Change and Estimated Components of Population Change: April 1, 2010 to July 1, 2017,” which contains measures of migration in United States counties; the “Educational Attainment for Adults Age 25 and Older for the U.S., States, and Counties, 1970-2016,” which contains measures of educational attainment in United States counties; and the “Annual County Resident Population Estimates by Age, Sex, Race, and Hispanic Origin: April 1, 2010 to July 1, 2017,” which contains a demographic breakdown of United States counties.

From the Bureau of Labor Statistics, this thesis incorporates data from “Unemployment and Median Household Income for the U.S. States and Counties, 2007-17,” which contains
measures of unemployment and median household income in United States counties. Rural-urban continuum codes for United States counties are also acquired from this dataset. From the Guardian and townhall.com, this thesis incorporates data from “County-Level Presidential General Election Results from 2012-2016,” which contains presidential election results in United States counties. From the Robert Wood Johnson Foundation, this thesis incorporates data from the “County Health Rankings National Data,” an annual examination of health outcomes in United States counties containing data on uninsured rates, violent crime rates, and residential segregation. And from the Association of Religion Data Archives, this thesis incorporates data from the “U.S. Religion Census: Religious Congregations and Membership Study, 2010,” which contains the results a once per decade study cataloguing the number of congregations and adherents of religious groups residing in United States counties.

This thesis also incorporates data from the Southern Poverty Law Center’s “Hate Map” from 2016 and 2017 to determine which hate groups were newly (re)activated in 2017. This was done by manually comparing the Southern Poverty Law Center’s listed hate groups in 2016 and their listed hate groups in 2017, identifying which hate groups appeared only in the 2017 data, and coding counties in the dataset with a dummy variable for the existence of a newly (re)activated right-wing hate group (0 = no right-wing hate group; 1 = right-wing hate group).

The compiled dataset, a product of the above individual datasets, incorporates data from all United States counties, yielding a sample size of 3,141 counties. However, individual datasets each include counties that had missing data, meaning the compiled dataset has bouts of missing data as well. Collectively, 587 counties were missing some data point important to the analysis. Counties with missing data were generally random; however, given missing data is often the product of a county’s failure to report data, small counties were particularly prone to having
missing data. Missing data was not an insignificant problem. Notably, every county in Alaska had missing data for at least one variable. However, rather than predicting these values, the observations with missing data were dropped instead, as estimating values for all missing data would be both strenuous and prone to inaccuracy. Additionally, dropping counties with missing data was required, due to this thesis’s use of matching methods. Had the data included NAHG counties with missing data, generating propensity scores and interpreting difference-in-mean treatment effects with missing values would have exposed the analysis to significant amounts of error. And had the data included non-NAHG counties with missing data, they would not have been utilized as matched units in the first place. However, because this thesis utilizes unit-to-unit comparisons, rather than comparisons of entire samples, it was not believed that these drops would meaningfully change the results. The final dataset used in this analysis yields a sample size of 2,554 counties, with 105 of them coded as NAHG counties.

Variables

The dependent variable of interest is HateGroup2017, which represents whether a county saw a newly (re)activated right-wing hate group in 2017. The outcomes for this variable are binary from 0 to 1, with 1 representing that a county is a NAHG county and 0 representing that a county is not.

The independent variables of interest include variables serving as proxies for economic anxiety, social anxiety, and cultural anxiety. To examine economic anxiety, Unemployment and Poverty are used as proxy variables. Unemployment denotes the unemployment rate in a United States county in 2016, and Poverty denotes the poverty rate in a United States county in 2016.
Both of these variables, Unemployment\textsuperscript{25,26} and Poverty\textsuperscript{27} have previously been used as proxies to gauge how economics can influence an individual’s involvement in a hate group. Therefore, this analysis will also incorporate those tested variables.

To examine social anxiety, Crime and Uninsured are used as proxy variables. Crime denotes the rate of violent crimes in a United States county in 2016, calculated by measuring the number of violent crimes per 100,000 people; and Uninsured denotes the uninsured rate in a United States county in 2016, represented by the percentage of the population under age 65 that lacks health insurance coverage. In previous studies examining hate groups, Crime\textsuperscript{28} has been used as a variable to determine its effect on the presence of white supremacist groups, but Uninsured has not. However, health care remains one of the highest priority issues in the United States,\textsuperscript{29} meaning the incorporation of the uninsured rate may capture social anxiety regarding the quality of life.

To examine cultural anxiety, NetMigration and ResidentialSegregation are used as proxy variables. NetMigration denotes the net number of domestic and international migrants per 1,000 people seen by a United States county in 2016; and ResidentialSegregation denotes the degree to which white and non-white groups live separate from one another in a United States county, calculated by taking the percentage of white or non-white residents that would have to move to

\textsuperscript{25} Rachel Durso and David Jacobs, "The Determinants of the Number of White Supremacist Groups," Social Problems 60, no. 1 (February 1, 2013), doi:10.1525/sp.2013.60.1.128.
\textsuperscript{28} Rachel Durso and David Jacobs, "The Determinants of the Number of White Supremacist Groups," 2013.
different geographic areas to match the racial distribution of the larger area. Neither
*ResidentialSegregation* nor *NetMigration* specifically appear as variables in other quantitative
analyses of hate groups; instead, demographics\textsuperscript{30,31} and other measures of immigration\textsuperscript{32} are
typically used. However, because *ResidentialSegregation* and *NetMigration* specifically capture
different types of cultural disconnectivity – *ResidentialSegregation* capturing racial
disconnectivity, and *NetMigration* capturing immigrant-based disconnectivity – they will be used
in this analysis.

The control variables used in the analysis include *Conservative, MedianIncome, White, NoCollege, Christian,* and *Rural.* *Conservative* denotes the percentage of the population that voted for Donald Trump in a United States county in the 2016 presidential election. *MedianIncome* denotes the median household income in a United States county in 2016. *White* denotes the percentage of the white population in a United States county in 2016. *NoCollege* denotes the percentage of the population in a United States county in 2016 that did not receive a college degree. *Christian* denotes the percentage of the population in a United States county in 2010 that adhered to any sect of Christianity. And *Rural* denotes whether a county in 2013 was deemed to be rural by the United States Department of Agriculture’s Economic Research Service. The outcomes for this variable range from 0 to 1, with 1 representing a rural county and 0 representing a non-rural county. Counties with rural-urban continuum codes of 8 or 9 are designated as rural, per the designations made by the USDA ERS. Interestingly, *Conservative, White, NoCollege,* and *Christian* appear as primary independent variables in previous analyses of

\textsuperscript{30} Rachel Durso and David Jacobs, "The Determinants of the Number of White Supremacist Groups," 2013.
\textsuperscript{31} Richard M. Medina et al., "Geographies of Organized Hate in America: A Regional Analysis," 2018.
hate group presence. However, this analysis will use them as controls, considering racial differences, education, and political affiliation are not the primary characteristics being studied, yet if left out, might inject omitted variable bias into the results. MedianIncome does not appear in previous analyses studying the presence of hate groups, but is a significant characteristic defining a county and will be used here to ensure no omitted variable bias appears in the results. Rural also does not appear in previous analyses studying the presence of hate groups; however, given the growing urban-rural divide, designating counties as rural adds an important dimension to the analysis.

Methods

To begin, this study conduct descriptive analysis by generating a statistical snapshot of the two samples utilized in this analysis: NAHG counties and non-NAHG counties. This will be done by identifying the average value of each variable of interest in each sample. Then, these average values will be compared to determine how the two samples differ from each other and identify which variables of interest are more present in each sample.

\[ \text{HateGroup2017}_i = \alpha \text{Unemployment}_i + \beta \text{Poverty}_i + \gamma \text{Crime}_i + \delta \text{Uninsured}_i + \eta \text{NetMigration}_i + \theta \text{ResidentialSegregation}_i + \lambda \text{Conservative}_i + \nu \text{MedianIncome}_i + \sigma \text{White}_i + \tau \text{NoCollege}_i + \rho \text{Christian}_i + \lambda \text{Rural}_i + \epsilon_i \]

Next, inferential analysis will be conducted. In its analysis, this thesis will assume the above equation, which denotes the probability a right-wing hate group was newly (re)activated in

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\[33\] Richard M. Medina et al., "Geographies of Organized Hate in America: A Regional Analysis," 2018.
a United States county in 2017. In the equation, $\alpha$, $\beta$, $\gamma$, $\delta$, $\eta$, and $\theta$ represent the coefficients of interest, while $i$ is the United States county.

First, propensity scores will be generated based on the controls Conservative, Median Income, White, No College, Christian, and Rural to match NAHG counties with non-NAHG counties. Then both nearest neighbor matching and Kernel matching will be conducted. This enables the analysis to isolate the effects of economic, cultural, and social anxiety, while separating the effects of sociodemographic characteristics, political leanings, and rurality. This would also mitigate the effects of dropped data, particularly when conducting Kernel matching. Nearest neighbor matching will be done with replacement and with bootstrap resampling.Kernel matching will also be done with bootstrap resampling.

Upon the completion of matching, differences will be calculated for each of the variables of interest between the matched units. This will determine whether the variables of interest are significantly different between the two units and will subsequently show whether the variables were significantly more present in NAHG counties.

To ensure that spillovers are not biasing the analysis, an additional sample will be tested. Significant worry exists that individuals in a county adjacent to a county with a newly (re)activated right-wing hate group may be less incentivized to create their own hate group, instead opting to join the adjacent county’s group. Capturing whether this spillover exists will be done by coding counties in the dataset with a dummy variable if there is a NAHG county directly adjacent to them ($0 =$ no adjacent NAHG county; $1 =$ adjacent NAHG county). Counties adjacent to NAHG counties will then be incorporated into a sensitivity sample. This considers how close in proximity two counties are to each other, incorporating that spatial dimension into matching.

34 Bootstrapping for both types of matching will be conducted with 50 replications
RESULTS

Descriptive Statistics

Table B1 presents a statistical snapshot of the sample of counties used in this analysis, stratified based on whether or not counties are NAHG counties. For the 105 NAHG counties, the average county had an unemployment rate of 4.81 percent and a poverty rate of 14.26 percent. The average NAHG county also had a crime rate of 402.35 violent crimes per 100,000 people, and an uninsured rate of 16.78 percent. Additionally, the average NAHG county had a net migration rate of 7.2 immigrants per 1,000 people and scored 37 on the residential segregation index. Finally, the average NAHG county had 49.49 percent of residents vote for Donald Trump in the 2016 election, a median income of $59,407.98, a white population totaling 76.12 percent of the total population, 39.10 percent of residents having no college education, and 45.19 percent of residents identifying as Christian. 2 percent of NAHG counties were rural.

Meanwhile, for the 2,554 United States counties that were not NAHG counties, the average county had an unemployment rate of 5.31 percent and a poverty rate of 16.05 percent. The average non-NAHG county also had a crime rate of 256.42 violent crimes per 100,000 people, and an uninsured rate of 17.17 percent. Additionally, the average non-NAHG county had a net migration rate of 0.17 immigrants per 1,000 people and scored 31.12 on the residential segregation index. Finally, the average non-NAHG county had 62.68 percent of residents vote for Donald Trump in the 2016 election, a median income of $49,500.55, a white population totaling 84.59 percent of the total population, 49.05 percent of residents having no college education, and 49.68 percent of residents identifying as Christian. 12 percent of non-NAHG counties were rural.
The difference in means between NAHG counties and non-NAHG counties indicates that NAHG counties had a higher crime rate, a higher net migration rate, a higher score on the residential segregation index, and a higher median income than non-NAHG counties. Conversely, NAHG counties had a lower unemployment rate, a lower poverty rate, a lower uninsured rate, fewer residents that voted for Donald Trump in the 2016 election, a smaller white population, a smaller population without a college education, and a lower Christian population compared to on-NAHG counties. NAHG counties were also slightly less rural than non-NAHG counties.

Figure A3 depicts the location of NAHG counties on a county-level map of the United States. Two things are of note. First, NAHG counties are spread throughout the United States, with NAHG counties present in all regions of the country. For example, NAHG counties can be found in states ranging from Texas to Florida to North Carolina. Second, NAHG counties are clustered in the areas they reside in. For example, Texas, Florida, and North Carolina each contain NAHG counties that border each other.

**Inferential Statistics**

**Matching**

Counties were matched based on six control characteristics: the percentage of voters that voted for Donald Trump, median income, the size of the white population, the percent of the population without a college education, the percent of the population that identifies as Christian, and rurality. After matching was completed, difference-in-mean treatment effects were obtained for the variables of interest: unemployment, poverty, the crime rate, the uninsured rate, the net migration rate, and residential segregation scores. Two different types of matching were
performed. First, nearest neighbor matching with replacement was used; second, Kernel matching was attempted. Table B2 shows the results of those tests.

The results of nearest neighbor matching are shown in Column 1 and illustrated in Figure A4. With nearest neighbor matching, every NAHG county was matched with a county that was not. The standard differences show that the average means of the NAHG counties and average means of the counties they were matched to were remarkably similar. In fact, the standard differences were less than 0.1 for all but one control variable—low even by conservative thresholds. The leftover control variable still had a standard difference less than 0.25—a more liberal threshold.

For markers of economic anxiety, matching revealed that the differences in unemployment and poverty rates between matched NAHG and non-NAHG counties, otherwise known as the difference-in-mean treatment effects (DTEs), were minimal, with the difference in the unemployment rate being -0.08 percent and the difference in the poverty rate being -1.21. Interestingly, this seems to indicate that counties that saw a right-wing new hate group in 2017 were stronger economically than their matched counterparts. Neither difference between NAHG and non-NAHG counties was statistically significant.

For markers of social anxiety, matching revealed that the DTEs for the crime rate and the uninsured rate between were somewhat significant. For the crime rate, the DTE was 92.97 crimes per 100,000 people and for the uninsured rate, the DTE was 1.54 percent. Both DTEs for the crime rate and uninsured rate were statistically significant at the 5 percent level.

And for markers of cultural anxiety, matching revealed the DTEs for the net migration rate and residential segregation index score were somewhat significant, with the DTE for the net migration rate being 4.45 immigrants per 1,000 people and the DTE for residential segregation
index scores being 1.87 points. Only the DTE for the net migration rate was statistically significant, and it was significant at the 1 percent level.

Nearest neighbor matching revealed that there were statistically significant DTEs for proxies of social and cultural anxiety between matched units. More specifically, the crime rate, uninsured rate, and net migration rate were higher in NAHG counties compared to their matched units.

Kernel matching was then conducted to ensure the results of nearest neighbor matching held across different types of matching. The results of Kernel matching are shown in Column 2 and illustrated in Figure A5. With Kernel matching, only 95 NAHG counties were matched. The standard differences were again small. The standard differences were less than 0.1 for four of the control variables, while the standard differences for the remaining two were less than 0.25.

For markers of economic anxiety, matching revealed that the DTEs for unemployment and poverty between the matched units were minimal, with the DTE for the unemployment rate being -0.11 percent and the DTE for the poverty rate being -0.58 percent. Again, this indicates that NAHG counties were stronger economically than their matched counterparts. Neither DTE was statistically significant.

For markers of social anxiety, matching revealed that the DTEs for the crime rate and the uninsured rate were significant, with the DTE for the crime rate being 78.51 crimes per 100,000 people and the DTE for the uninsured rate being 1.11 percent. Both were statistically significant, with the DTE for the crime rate being significant at the 1 percent level and the DTE for the uninsured rate being significant at the 10 percent level.

And for markers of cultural anxiety, matching revealed the DTEs for the net migration rate and residential segregation index score were also significant. For the net migration rate, the
DTE was 4.83 immigrants per 1,000 people and for the residential segregation index score, the DTE was 1.77 points. Only the DTE for the net migration rate was statistically significant, and it was significant at the 1 percent level.

Kernel matching revealed that there were statistically significant DTE for proxies of social and cultural anxiety between matched units. More specifically, the crime rate, uninsured rate, and net migration rate were higher in NAHG counties compared to their matched units.

For both types of matching, the statistically significant DTEs were identical—the DTEs for the crime rate, the uninsured rate, and the net migration rate were all statistically significant. Ultimately, matching indicates that markers of social anxiety and cultural anxiety were significantly higher in NAHG counties. Additionally, economic anxiety was not significantly more present in NAHG counties compared to non-NAHG counties.

**Additional Analyses**

Two additional analyses were performed to obtain more specificity and clarity from the achieved results. These two analyses included using longitudinal economic variables as proxies for economic anxiety and stratifying matching based on hate group type.

First, there exist concerns that the proxies for economic anxiety may be insufficient because they are static variables. In other words, the unemployment rate and poverty rate used were specifically from 2016. However, economic anxiety may be better captured longitudinally. While an economic snapshot from 2016 may hold significance, so too does analyzing a county’s economic recovery from the 2008 financial crash. Considering many have argued the radicalization of the right was informed by the ability for areas to economically recover, this is particularly important to consider in this analysis.
To test this, trend variables were created for the unemployment rate and the poverty rate. These variables were created by taking the unemployment and poverty rates from 2007 and subtracting them by the unemployment and poverty rates from 2016.

Table B3 shows the results that were obtained when economic trend variables were used in nearest neighbor and Kernel matching. Those results are represented in Columns 1 and 2 and illustrated in Figures A6 and A7, respectively.

As both columns indicate, even when using longitudinal economic variables, the DTEs for the unemployment rate and poverty rate are still not statistically significant. This reaffirms that economic anxiety, in all its dimensions and forms, was not significantly more present in NAHG counties compared to non-NAHG counties.

Second, right-wing hate groups are not a homogenous block. Instead, groups subscribe to different ideologies and have different populations they target. Therefore, it seemed valuable to perform matching with stratified samples. To do so, four smaller samples were constructed. These samples contained counties that saw re(activated) hate groups representing the four most prominent factions of right-wing hate groups: anti-immigrant groups, anti-Muslim groups, neo-Nazis, and white supremacists. The results of matching for those four samples are contained in Table B4.

It should be noted that this stratified analysis suffers from small sample sizes. The number of counties that saw newly (re)activated anti-immigrant, neo-Nazi, and white supremacist hate groups is small – under the 30-sample size threshold. As a result, a layer of caution should be placed on generalizing or placing confidence in these results. Despite this, attempting to uncover the motivations of specific hate group ideologies was still deemed worthwhile and therefore was pursued.
Columns 1 and 2 show the results of nearest neighbor and Kernel matching for counties that saw newly (re)activated anti-Muslim hate group in 2017. The results of nearest neighbor and Kernel matching are also illustrated in Figures A8 and A9, respectively. The results show that for counties with newly (re)activated anti-Muslim groups, the DTEs for the uninsured rate and the net migration rate were statistically significant.

For nearest neighbor matching, the results of which are in Column 1, the DTEs for the uninsured rate and net migration rate were statistically significant at the 5 percent and 10 percent level, respectively. For Kernel matching, the results of which are in Column 2, the DTEs for the unemployment rate and net migration rate were also statistically significant, both at the 1 percent level. These results indicate that counties that saw a newly (re)activated anti-Muslim hate group in 2017 had significantly higher levels of social and cultural anxiety compared to those that did not.

Columns 3 and 4 show the results of nearest neighbor and Kernel matching for counties that saw a newly (re)activated white supremacist hate group in 2017. The results of nearest neighbor and Kernel matching are also illustrated in Figures A10 and A11, respectively. The results show that for counties with newly (re)activated white supremacist groups, the DTEs for the crime rate, the net migration rate, the uninsured rate, and the residential segregation score were statistically significant.

For nearest neighbor matching, the results of which are in Column 3, the DTEs for the crime rate, net migration rate, and residential segregation score were all statistically significant at the 5 percent level. For Kernel matching, the results of which are in Column 4, the DTEs for the uninsured rate and the net migration rate were both statistically significant at the 5 percent level.
These results indicate social anxiety and cultural anxiety were more present in counties that saw newly (re)activated white supremacist hate groups in 2017.

Columns 5 and 6 show the results of nearest neighbor and Kernel matching for counties that saw a newly (re)activated neo-Nazi hate group in 2017. The results of nearest neighbor and Kernel matching are also illustrated in Figures A12 and A13, respectively. The results show that for counties with newly (re)activated neo-Nazi groups, no DTEs for proxies of economic, social, or cultural anxiety were statistically significant. In other words, anxiety of all kinds was not significantly more present in counties that saw a newly (re)activated neo-Nazi hate group in 2017 compared to their matched counterparts.

Columns 7 and 8 show the results of nearest neighbor and Kernel matching for counties that saw a newly (re)activated anti-immigrant hate group in 2017. The results of nearest neighbor and Kernel matching are also illustrated in Figures A14 and A15, respectively. Like for counties with newly (re)activated neo-Nazi groups, the results show that for counties with newly (re)activated anti-immigrant groups, no DTEs for proxies of economic, social, or cultural anxiety were statistically significant. In other words, anxiety of all kinds was not significantly more present in counties that saw a newly (re)activated anti-immigrant hate group in 2017 compared to their matched counterparts.

Sensitivity Test

A sensitivity test was conducted to minimize spillover effects that might impact the DTEs obtained from matching. Spillover effects are likely, as the influence of a hate group is not contained solely within a county’s boundaries. Residents in surrounding counties, motivated by the conditions of where they live, can also participate in these hate groups. Thus, accounting for these individuals requires considering both NAHG counties, as well as all adjacent counties who
can participate in those hate groups. Therefore, a new sample was constructed incorporating counties that were influenced by a newly (re)activated right-wing hate group in 2017, referred to as “NIHG counties.”

Table B5 presents a statistical snapshot of this new sample, stratified based on whether a county is a NIHG county. Despite the sample expanding to 445 counties, the difference in means between NIHG counties and non-NIHG counties follow a similar pattern to the original sample. While the magnitudes of those differences are different, NIHG counties still had a higher crime rate, a higher net migration rate, a higher residential segregation score, and a higher median income compared to non-NIHG counties.

This sample was matched in identical ways as before, both in terms of variables matched and the dual methods of matching. The results of those tests are shown in Table B6.

The results of nearest neighbor matching are shown in Column 1 and illustrated in Figure A16. With nearest neighbor matching, every NIHG county was matched with a non-NIHG county. The standard differences were less than 0.1 for all six control variables.

The DTEs for nearest neighbor matching on the sensitivity sample followed a similar pattern of statistical significance as the original matching tests. For markers of economic anxiety, neither were statistically significant. For markers of social anxiety, the DTEs for the crime rate and the uninsured rate were statistically significant at the 5 percent and 1 percent level, respectively. For markers of cultural anxiety, the DTEs for the net migration rate and residential segregation score were statistically significant at the 5 percent and 1 percent level, respectively.

Nearest neighbor matching for NIHG counties displayed similar results as when nearest neighbor matching was performed for NAHG counties. In both samples, the DTEs for the crime
rate, uninsured rate, and net migration rate were statistically significant. However, the DTE for the residential segregation scores was only significant in the NIHG sample.

The results of Kernel matching are shown in Column 2 and illustrated in Figure A17. With Kernel matching, 414 NIHG counties were matched. The standard differences were less than or equal to 0.1 for all six control variables.

The DTEs for Kernel matching on the sensitivity sample also followed a similar pattern of statistical significance as the original matching tests. For markers of economic anxiety, neither were statistically significant. For markers of social anxiety, the DTEs for both the crime rate and uninsured rate were statistically significant at the 1 percent and 5 percent level, respectively. For markers of cultural anxiety, the DTEs for both the net migration rate and residential segregation index score were statistically significant at the 1 percent level.

Like with nearest neighbor matching, Kernel matching for NIHG counties displayed similar results as when Kernel matching was performed for NAHG counties. In both samples, the DTEs for the crime rate, uninsured rate, and net migration rate were statistically significant. However, the DTE for the residential segregation score was only significant in the NIHG sample.

When expanding the sample and including NIHG counties, the results from the original test hold. The DTEs for the crime rate, uninsured rate, and net migration rate were statistically significant across both types of matching and across both samples. Additionally, the lack of statistical significance of the DTEs for the unemployment rate and the poverty rate is present in all tests. However, the results do show inconsistencies between the samples regarding the statistical significance of the DTE for the residential segregation index score. Despite this, including NIHG counties reaffirms that significantly higher levels of social and cultural anxiety
existed where 2017’s hate groups were (re)activated and that levels of economic anxiety were not significantly greater.

**DISCUSSION**

This study sought to understand whether NAHG counties experienced higher levels of economic, social, and cultural anxiety compared to non-NAHG counties. To test this, nearest neighbor and Kernel matching were used. The results indicate that while social and cultural anxiety were significantly higher in NAHG counties, economic anxiety was not. Subsequently, while the results are consistent with break-out hypotheses (ii) and (iii), the absence of significantly higher economic anxiety in NAHG counties means hypothesis (i) was not supported by the findings. The results offer numerous opportunities for continued discussion.

*Policy Implications*

**Shifting Ideology**

The discovery that cultural and social anxiety, and not economic anxiety, were significantly more present in NAHG counties may reflect an ideological shift in the radical right. Studies have verified that racial animus is amplified during times of economic downturn, especially pronounced in anti-immigrant messaging that largely focuses on the negative impacts of immigration on employment. Given this, it would be reasonable to believe that economic anxiety would play a role in the (re)activation of right-wing hate groups. However, the results indicate that this was not true in NAHG counties.

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While it could be argued that this inconsistency points to errors in the results, there may be another viable explanation. As a reminder, the sample selected for this analysis attempts to understand what motivated hate group development specifically in 2017—a year in which the conversations in the right-wing extremist communities underwent a notable shift. From Donald Trump’s continued proclamation that Mexican immigrants are “…bringing drugs… crimes… [and are] rapists”\textsuperscript{36} to right-wing extremists’ renewed fears of a white genocide\textsuperscript{37}, messaging around right-wing extremism has shifted decidedly away from economics and towards social and cultural concerns. This has only been amplified by recent right-wing incidents that were driven by social and cultural concerns, but devoid of economic motivations.

Social and cultural fears are far more potent than economic concerns, and the indication that right-wing extremists may be modifying their ideology should be cause for worry. Such a change in motivations may imply that the traditional framework for understanding these groups has become outdated and that these groups are far more malleable in their positions and ideologies than has been previously acknowledged.

**The Need for Authoritative Research**

While the sample used in this study seeks to specifically understand the motivations of hate groups that were created or activated during the Trump presidency, it is curious that the results do not match previous studies. Specifically, previous analyses of hate groups have found that economic conditions were predictors for the presence of hate groups—a conclusion this study did not reach.


As previously discussed, research efforts on right-wing extremism and hate groups on a federal level have been dramatically reduced. However, these conflicting findings may indicate the need for a revitalization of research efforts. For example, while Durso and Jacobs (2013) found that unemployment rates significantly affected the presence of white supremacist groups, this study found that unemployment rates were not significantly higher in NAHG counties. Additionally, while Medina, Nicolosi, Brewer, and Linke (2018) found that poverty rates were positively correlated with the presence of hate groups, this thesis found that poverty rates were not significantly higher in NAHG counties. Moreover, a March 2009 F.B.I. briefing on right-wing radicalization, one of the last federal briefings on right-wing radicalization released publically, theorized that heightened stress from the financial crisis was a prominent driver for right-wing radicalization. However, again, this thesis found that economic anxiety was not significantly higher in NAHG counties.

The conflicting results from this thesis and related literature seem to indicate that there is not an anachronistic explanation that can explain the presence of hate groups, and so a more dynamic framework must be established. But without research capabilities to understand or uncover that framework, the most current motivations of hate groups will continue to be hidden in the dark. If motivations are shifting for hate groups, and have shifted recently, relying on a model that emphasizes economic anxiety may no longer be sufficient. Therefore, more research will be required.

Hate groups continue to be a threat to racial, sexual, and gender minorities in the United States. And without adequate understanding of these groups, that threat will persist and grow.

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38 Reitman, "U.S. Law Enforcement Failed to See the Threat of White Nationalism. Now They Don't Know How to Stop It."
Therefore, revitalizing a dedicated, authoritative effort to research hate groups may be critical in the future.

Limitations

Several limitations of this study are worth recognizing, including concerns over SPLC data and the absence of individual-level data. First, concerns exist regarding the use of the SPLC’s hate group data. While the SPLC compiles the most comprehensive data on hate groups in the United States, criticism has been directed at the organization regarding their designation of hate groups. In fact, many have argued that the SPLC is facing a crisis of credibility as SPLC-designated hate groups have voiced opposition to their designations. As a result, there is a fair concern that the SPLC data used in this study may not accurately represent the hate group landscape and may overestimate their presence. However, given the SPLC is the only group actively compiling annual data on hate groups, it remains the only viable source of data from which this analysis could have been conducted.

Second, this study was absent of individual-level data for counties. This analysis was conducted on the county-level, because of the easier availability of data. However, as noted in the conceptual framework, the true mechanisms of radicalization occur on the individual level. Presumably, county-level data may not adequately reflect the lifestyles and well-being of the individuals that choose to join hate groups—especially considering hate group members comprise a small percentage of a county’s population. Individual-level data would have been helpful in providing more specificity in the results, had such data been available. Unfortunately, such data was not accessible.

Areas for Future Research

Future studies seeking to build on hate group research should focus on the following: the incorporation of 2018 data and the use of data on hate crimes and lone wolf attacks.

First, subsequent studies should incorporate 2018 data to ensure that the results obtained in this study persist. This study specifically focused on 2017 to isolate the “Trump effect” on hate groups, but that effect presumably continued to influence hate groups in 2018. Efforts to verify this would be valuable. As of the time of this writing, the SPLC has just released their 2018 data, and incorporating these new groups may help to validate or challenge these results. Ultimately, it is worth investigating whether this study tracked an anomaly or a new trend in hate group motivations.

Second, subsequent studies should use data on hate crimes and lone wolf attacks. While right-wing extremists have coalesced into organizations like hate groups, individual actions and attacks also comprise a significant amount of right-wing activity. In fact, disassociation from organized groups is a key feature of right-wing extremists, especially for individuals identifying as white supremacists. Therefore, incorporating data on actions committed by individuals, such as hate crimes or lone wolf attacks, may provide insight into a significant portion of right-wing activity that has been even more understudied.

CONCLUSION

After historic growth in hate groups in 2017, the SPLC revealed that trends in 2018 were no different. The United States is now home to a record high number of hate groups within its

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borders. This study attempted to pierce a veil, working to uncover the motivations of right-wing hate groups that have historically been under-researched. But there is certainly more work to be done. Hate groups are continuing to grow at unprecedented rates. We should be sure that our understanding of them continues to grow as well.

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FIGURE A1: The Staircase Model of Terrorism

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FIGURE A2: The Conceptual Model
FIGURE A3: Map of NAHG Counties
FIGURE A4: Balancing Box Plot for Nearest Neighbor Matching with NAHG and Non-NAHG Counties
FIGURE A5: Balancing Box Plot for Kernel Matching with NAHG and Non-NAHG Counties
FIGURE A6: Balancing Box Plot for Nearest Neighbor Matching with NAHG and Non-NAHG Counties Using Longitudinal Economic Variables
FIGURE A7: Balancing Box Plot for Kernel Matching with NAHG and Non-NAHG Counties Using Longitudinal Economic Variables
FIGURE A8: Balancing Box Plot for Nearest Neighbor Matching with Counties without (Re)Activated Anti-Muslim Groups and Counties with (Re)Activated Anti-Muslim Groups
FIGURE A9: Balancing Box Plot for Kernel Matching with Counties without (Re)Activated Anti-Muslim Groups and Counties with (Re)Activated Anti-Muslim Groups
FIGURE A10: Balancing Box Plot for Nearest Neighbor Matching with Counties without (Re)Activated White Supremacist Groups and Counties with (Re)Activated White Supremacist Groups
FIGURE A11: Balancing Box Plot for Kernel Matching with Counties without (Re)Activated White Supremacist Groups and Counties with (Re)Activated White Supremacist Groups
FIGURE A12: Balancing Box Plot for Nearest Neighbor Matching with Counties without (Re)Activated Neo-Nazi Groups and Counties with (Re)Activated Neo-Nazi Groups
FIGURE A13: Balancing Box Plot for Kernel Matching with Counties without (Re)Activated Neo-Nazi Groups and Counties with (Re)Activated Neo-Nazi Groups
FIGURE A14: Balancing Box Plot for Nearest Neighbor Matching with Counties without (Re)Activated Anti-Immigrant Groups and Counties with (Re)Activated Anti-Immigrant Groups
FIGURE A15: Balancing Box Plot for Kernel Matching with Counties without (Re)Activated Anti-Immigrant Groups and Counties with (Re)Activated Anti-Immigrant Groups
FIGURE A16: Balancing Box Plot for Nearest Neighbor Matching with NIHG and Non-NIHG Counties
FIGURE A17: Balancing Box Plot for Kernel Matching with NIHG and Non-NIHG Counties
APPENDIX B: TABLES

TABLE B1: Descriptive Statistics for NAHG and Non-NAHG Counties

<table>
<thead>
<tr>
<th>Variable</th>
<th>NAHG Counties</th>
<th>Non-NAHG Counties</th>
<th>Difference in Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment (in percent)</td>
<td>4.81</td>
<td>5.31</td>
<td>-0.50</td>
</tr>
<tr>
<td>Poverty (in percent)</td>
<td>14.26</td>
<td>16.05</td>
<td>-1.79</td>
</tr>
<tr>
<td>Crime (in number of crimes per 100,000 people)</td>
<td>402.35</td>
<td>256.42</td>
<td>145.93</td>
</tr>
<tr>
<td>Uninsured (in percent)</td>
<td>16.78</td>
<td>17.17</td>
<td>-0.39</td>
</tr>
<tr>
<td>Net Migration Rate (in number of immigrants per 1,000 people)</td>
<td>7.20</td>
<td>0.17</td>
<td>7.03</td>
</tr>
<tr>
<td>Residential Segregation (in index score)</td>
<td>37.00</td>
<td>31.12</td>
<td>5.88</td>
</tr>
<tr>
<td>Conservative (in percent)</td>
<td>49.49</td>
<td>62.68</td>
<td>-13.19</td>
</tr>
<tr>
<td>Median Income (in dollars)</td>
<td>59407.98</td>
<td>49500.55</td>
<td>9907.43</td>
</tr>
<tr>
<td>White (in percent)</td>
<td>76.12</td>
<td>84.59</td>
<td>-8.47</td>
</tr>
<tr>
<td>No College (in percent)</td>
<td>39.10</td>
<td>49.05</td>
<td>-9.95</td>
</tr>
<tr>
<td>Christian (in percent)</td>
<td>45.19</td>
<td>49.68</td>
<td>-4.49</td>
</tr>
<tr>
<td>Rural (in percent)</td>
<td>0.02</td>
<td>0.12</td>
<td>-0.1</td>
</tr>
</tbody>
</table>

Sources: Model-based Small Area Income and Poverty Estimates [MSAIPE], Population Change and Estimated Components of Population Change: April 1, 2010 to July 1, 2017 [PCECPC], Educational Attainment for Adults Age 25 and Older for the U.S., States, and Counties, 1970-2016 [EAA], Annual County Resident Population Estimates by Age, Sex, Rate, and Hispanic Origin: April 1, 2010 to July 1, 2017 [ACRPE], Unemployment and Median Household Income for the U.S. States and Counties, 2007-17 [UMHI], County-Level Presidential General Election Results from 2012-2016 [CLPGER], County Health Rankings National Data [CHRND], and U.S. Religion Census: Religious Congregations and Membership Study, 2010 [USRCRCMS]
### TABLE B2: Difference-in-Means Treatment Effects for NAHG and Non-NAHG Counties

<table>
<thead>
<tr>
<th>Difference-in-Means Treatment Effect</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment</td>
<td>-0.08</td>
<td>-0.11</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.15)</td>
</tr>
<tr>
<td>Poverty</td>
<td>-1.21</td>
<td>-0.58</td>
</tr>
<tr>
<td></td>
<td>(0.97)</td>
<td>(0.64)</td>
</tr>
<tr>
<td>Crime</td>
<td>92.97**</td>
<td>78.51***</td>
</tr>
<tr>
<td></td>
<td>(38.62)</td>
<td>(28.90)</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.54**</td>
<td>1.11*</td>
</tr>
<tr>
<td></td>
<td>(0.76)</td>
<td>(0.64)</td>
</tr>
<tr>
<td>Net Migration</td>
<td>4.45**</td>
<td>4.83***</td>
</tr>
<tr>
<td></td>
<td>(2.22)</td>
<td>(1.48)</td>
</tr>
<tr>
<td>Residential Segregation</td>
<td>1.87</td>
<td>1.77</td>
</tr>
<tr>
<td></td>
<td>(2.16)</td>
<td>(1.67)</td>
</tr>
</tbody>
</table>

#### Standard Differences

<table>
<thead>
<tr>
<th></th>
<th>1</th>
<th>2</th>
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</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>0.03</td>
<td>-0.01</td>
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<tr>
<td>Median Income</td>
<td>0.04</td>
<td>0.14</td>
</tr>
<tr>
<td>White</td>
<td>0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>No College</td>
<td>-0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Christian</td>
<td>0.17</td>
<td>-0.12</td>
</tr>
<tr>
<td>Rural</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

| Matched Units            | 105      | 95       |

Sources: MSAIPE, PCECPC, EAA, ACRPE, UMHI, CLPGER, CHRND, and USRCRCMS

Note: * p < 0.1, ** p < 0.05, *** p < 0.01
TABLE B3: Difference-in-Means Treatment Effects for NAHG and non-NAHG Counties Using Longitudinal Economic Variables

<table>
<thead>
<tr>
<th>Difference-in-Means Treatment Effect</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Trend</td>
<td>-0.27</td>
<td>-0.18</td>
</tr>
<tr>
<td></td>
<td>(0.38)</td>
<td>(0.32)</td>
</tr>
<tr>
<td>Poverty Trend</td>
<td>-0.21</td>
<td>-0.05</td>
</tr>
<tr>
<td></td>
<td>(0.25)</td>
<td>(0.25)</td>
</tr>
<tr>
<td>Crime</td>
<td>92.97***</td>
<td>78.51***</td>
</tr>
<tr>
<td></td>
<td>(34.99)</td>
<td>(25.20)</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.54*</td>
<td>1.11*</td>
</tr>
<tr>
<td></td>
<td>(0.83)</td>
<td>(0.66)</td>
</tr>
<tr>
<td>Net Migration</td>
<td>4.45**</td>
<td>4.83***</td>
</tr>
<tr>
<td></td>
<td>(2.04)</td>
<td>(1.32)</td>
</tr>
<tr>
<td>Residential Segregation</td>
<td>1.87</td>
<td>1.77</td>
</tr>
<tr>
<td></td>
<td>(2.22)</td>
<td>(1.67)</td>
</tr>
</tbody>
</table>

**Standard Differences**

<table>
<thead>
<tr>
<th>Conservative</th>
<th>0.03</th>
<th>-0.01</th>
</tr>
</thead>
<tbody>
<tr>
<td>Median Income</td>
<td>0.04</td>
<td>0.14</td>
</tr>
<tr>
<td>White</td>
<td>0.04</td>
<td>-0.02</td>
</tr>
<tr>
<td>No College</td>
<td>-0.02</td>
<td>0.04</td>
</tr>
<tr>
<td>Christian</td>
<td>0.17</td>
<td>0.12</td>
</tr>
<tr>
<td>Rural</td>
<td>-0.04</td>
<td>-0.04</td>
</tr>
</tbody>
</table>

Matched Units: 105, 95

Sources: MSAIPE, PCECPC, EAA, ACRPE, UMHI, CLPGER, CHRND, and USRCRCMS

Note: * p < 0.1, ** p < 0.05, *** p < 0.01
TABLE B4: Difference-in-Means Treatment Effects for NAHG Counties and Non-NAHG Counties, Stratified by Type of Hate Group

<table>
<thead>
<tr>
<th>Difference-in-Means Treatment Effect</th>
<th>Anti-Muslim</th>
<th>White Supremacist</th>
<th>Neo-Nazi</th>
<th>Anti-Immigrant</th>
</tr>
</thead>
<tbody>
<tr>
<td>Treatment Effect</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemployment</td>
<td>-0.43***</td>
<td>-0.43***</td>
<td>-0.09**</td>
<td>0.69***</td>
</tr>
<tr>
<td></td>
<td>(0.35)</td>
<td>(0.35)</td>
<td>(0.21)</td>
<td>(0.61)</td>
</tr>
<tr>
<td>Poverty</td>
<td>-0.38**</td>
<td>-0.38**</td>
<td>-0.07**</td>
<td>2.22**</td>
</tr>
<tr>
<td></td>
<td>(1.25)</td>
<td>(1.25)</td>
<td>(1.21)</td>
<td>(2.54)</td>
</tr>
<tr>
<td>Crime</td>
<td>88.85***</td>
<td>88.85***</td>
<td>190.27***</td>
<td>22.11**</td>
</tr>
<tr>
<td></td>
<td>(66.07)</td>
<td>(66.07)</td>
<td>(88.94)</td>
<td>(86.59)</td>
</tr>
<tr>
<td>Uninsured</td>
<td>3.09***</td>
<td>3.09***</td>
<td>2.50**</td>
<td>1.67**</td>
</tr>
<tr>
<td></td>
<td>(1.51)</td>
<td>(1.51)</td>
<td>(1.88)</td>
<td>(2.97)</td>
</tr>
<tr>
<td>Net Migration</td>
<td>6.41**</td>
<td>6.41*</td>
<td>9.56**</td>
<td>9.75**</td>
</tr>
<tr>
<td></td>
<td>(3.44)</td>
<td>(3.44)</td>
<td>(4.05)</td>
<td>(6.49)</td>
</tr>
<tr>
<td>Residential Segregation</td>
<td>-1.00</td>
<td>-1.00</td>
<td>9.64**</td>
<td>-2.56</td>
</tr>
<tr>
<td></td>
<td>(3.90)</td>
<td>(3.90)</td>
<td>(4.78)</td>
<td>(6.37)</td>
</tr>
</tbody>
</table>

| Standard Differences               |             |                   |          |               |
| Conservative                       | -0.04       | -0.04             | -0.18    | 0.28          |
|                                     | (0.13)      | (0.13)            | (0.42)   | (0.18)        |
| White                               | 0.18        | 0.18              | -0.15    | -0.13         |
|                                     | 0           | 0                 | 0.19     | 0.02          |
| No College                          | 0           | 0                 | 0.19     | -0.14         |
| Christian                           | -0.39       | -0.39             | 0.39     | 0.07          |
|                                     | 0.07        | 0.07              | 0.07     | 0.09          |
| Rural                               | 0           | 0                 | 0        | 0             |
| Matched Units                       | 34          | 34                | 22       | 9             |

Sources: MSAIPE, PCECPC, EAA, ACRPE, UMHI, CLPGER, CHRND, and USRCRCMS
Note: * p < 0.1, ** p < 0.05, *** p < 0.01
### TABLE B5: Descriptive Statistics for NIHG Counties and Non-NIHG Counties

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Mean</th>
<th>Standard Deviation</th>
<th>Difference in Means</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment (in percent)</td>
<td>5.12</td>
<td>1.78</td>
<td>5.33</td>
<td>1.74</td>
<td>-0.21</td>
</tr>
<tr>
<td>Poverty (in percent)</td>
<td>14.53</td>
<td>5.68</td>
<td>16.27</td>
<td>6.12</td>
<td>-1.74</td>
</tr>
<tr>
<td>Crime (in number of crimes per 1,000 people)</td>
<td>300.24</td>
<td>219.59</td>
<td>254.53</td>
<td>191.48</td>
<td>45.71</td>
</tr>
<tr>
<td>Uninsured (in percent)</td>
<td>16.91</td>
<td>5.29</td>
<td>17.20</td>
<td>5.26</td>
<td>-0.29</td>
</tr>
<tr>
<td>Net Migration Rate (in number of immigrants per 1,000 people)</td>
<td>4.84</td>
<td>10.75</td>
<td>-0.43</td>
<td>11.91</td>
<td>5.27</td>
</tr>
<tr>
<td>Residential Segregation (in index score)</td>
<td>34.21</td>
<td>11.87</td>
<td>30.78</td>
<td>13.27</td>
<td>3.43</td>
</tr>
<tr>
<td>Conservative (in percent)</td>
<td>58.14</td>
<td>16.39</td>
<td>62.96</td>
<td>15.15</td>
<td>-4.82</td>
</tr>
<tr>
<td>Median Income (in dollars)</td>
<td>55705.62</td>
<td>15768.51</td>
<td>48723.23</td>
<td>12294.17</td>
<td>6982.39</td>
</tr>
<tr>
<td>White (in percent)</td>
<td>81.75</td>
<td>15.80</td>
<td>84.76</td>
<td>15.69</td>
<td>-3.01</td>
</tr>
<tr>
<td>No College (in percent)</td>
<td>45.08</td>
<td>10.95</td>
<td>49.37</td>
<td>10.54</td>
<td>-4.29</td>
</tr>
<tr>
<td>Christian (in percent)</td>
<td>45.35</td>
<td>14.46</td>
<td>50.33</td>
<td>18.28</td>
<td>-4.98</td>
</tr>
<tr>
<td>Rural (in percent)</td>
<td>0.04</td>
<td>0.19</td>
<td>0.13</td>
<td>0.34</td>
<td>-0.09</td>
</tr>
<tr>
<td>N</td>
<td>445</td>
<td></td>
<td>2,214</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Sources: MSAIPE, PCECPC, EAA, ACRPE, UMHI, CLPGER, CHRND, and USRCRCMS
### TABLE B6: Difference-in-Means Treatment Effects for NIHG Counties and Non-NIHG Counties

<table>
<thead>
<tr>
<th>Difference-in-Means Treatment Effect</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment</td>
<td>0.01 (0.12)</td>
<td>0.067 (0.10)</td>
</tr>
<tr>
<td>Poverty</td>
<td>-0.13 (0.34)</td>
<td>0.16 (0.29)</td>
</tr>
<tr>
<td>Crime</td>
<td>36.29** (16.35)</td>
<td>49.36*** (13.89)</td>
</tr>
<tr>
<td>Uninsured</td>
<td>1.05*** (0.38)</td>
<td>0.77** (0.34)</td>
</tr>
<tr>
<td>Net Migration</td>
<td>4.61*** (1.08)</td>
<td>3.41*** (0.75)</td>
</tr>
<tr>
<td>Residential Segregation</td>
<td>2.29** (1.09)</td>
<td>2.98*** (0.74)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Standard Differences</th>
<th>1</th>
<th>2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative</td>
<td>0.02</td>
<td>-0.05</td>
</tr>
<tr>
<td>Median Income</td>
<td>0.03</td>
<td>0.01</td>
</tr>
<tr>
<td>White</td>
<td>-0.01</td>
<td>-0.04</td>
</tr>
<tr>
<td>No College</td>
<td>-0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>Christian</td>
<td>0.05</td>
<td>0.04</td>
</tr>
<tr>
<td>Rural</td>
<td>0.02</td>
<td>0</td>
</tr>
</tbody>
</table>

| Matched Units                        | 445        | 414        |

Sources: MSAIPE, PCEPCC, EAA, ACRPE, UMHI, CLPGER, CHRND, and USRCRCMS

Note: * p < 0.1, ** p < 0.05, *** p < 0.01
BIBLIOGRAPHY


