Watching Hate – Social Instability as a Factor for the Presence of Hate Groups in US Counties

Flora Worthington

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Washington and Lee University

Advisor: Professor Katharine Shester

Committee Members: Professor Joseph Guse and Professor Michael Anderson

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Abstract:
Hate groups in the United States form a pressing problem and have been examined in quantitative economic and sociological research. In this paper, I analyze predictors of hate groups, particularly age-adjusted mortality as a proxy for deaths of despair. Case and Deaton noted that, via deaths of despair (deaths through alcohol, drugs, or suicide), age-adjusted mortality for white Americans has increased in recent years. This variable could serve as a proxy for social disruption in communities. This disruption may, in turn, factor into the fear that theoretically drives these hate groups. Using a long-term analysis of the Southern Poverty Law Center's list of hate groups in their "Hate Map," this study tests new variables not examined in prior literature, as well as tests the robustness of prior results. This study finds that while increased deaths are correlated with the presence of a hate group in a county, they are negatively correlated with the number of hate groups in a given county. These results, in combination with other findings and the work of other scholars, suggest that hate groups are a product of both social disruption and social cohesion.

I. Introduction and Background

Hate groups have risen in visibility in recent years, particularly since 2016 with the election of Donald Trump. Events such as the Charlottesville “Unite the Right” rally in 2017 and January 6th insurrection in 2020 demonstrate the danger these groups pose to individual lives and to the United States as a whole. Understanding how and where hate groups form and stay should be an important focus of research and policy.

Variables which measure social disruption or decline in quality of life for the community (Boyd 2022, 2) show an interruption in the status quo which could contribute to the presence of hate groups. One variable which could measure this decrease in quality of life could be deaths of despair – a term coined by Case and Deaton in 2015. Deaths of despair refer to deaths by alcohol, drugs, or self-harm, which have been on the rise in the United States, particularly for less educated, non-Hispanic white men (Case and Deaton 2015). These deaths are associated with other socioeconomic disruptions, such as the introduction of fracking which changes the fabric and composition of a community in a rapid way (Boyd 2022). The Southern Poverty Law Center (SPLC) publishes a regular list of the locations of hate groups which several studies use, but to the best of my knowledge deaths of despair have not been studied in this context.

However, several hypotheses explaining the presence of hate groups do exist, with the primary question being to what degree groups require a sense of racial threat versus the resources necessary to maintain these organizations. Examining the relationship between deaths of despair and controlling for variables other writers found significant could advance scholarship in this field. Using age-adjusted mortality for certain age groups as a proxy for deaths of despair, this paper finds a positive relationship between the presence of hate groups and the number of deaths and despair, but a negative correlation between the number of hate groups in a given county and the number of deaths of despair suggesting a requirement for both perceived deprivation and adequate resources for the formation of hate groups.

II. Literature Review

The work of Jefferson and Pryor (1999) was the earliest research I could find to use the dataset of the Southern Poverty Law Center. Their logit analysis and the paper's conclusion, that "sociological or economic explanations for the existence of hate groups in an area are far less important than… history and particular conditions," has formed much of the framework for debate and discussion since their publication (Jefferson and Pryor 1999, 394). In their county-level analysis of SPLC data from 1997, the authors found that historical factors, such as whether a state joined the Confederacy in 1861, were highly significant correlates with whether a county had the presence of a hate group. Counties which joined the Confederacy in 1861were approximately 5% more likely to have a hate group than counties in states which did not secede from the Union. Population density in a county was also significant, both economically and statistically. However, socioeconomic variables such as racial composition, unemployment, or divorce rates were not found to be statistically significant (Jefferson and Pryor 1999, 392). Their regression used a simple indicator variable for the presence of a hate group in a county, rather than a variable measuring multiple hate groups, which treats counties with vastly different levels of hate groups in them identically. Their dataset only contains one year's worth of information, which makes sense given when the article was published, but obviously prevents tracking changes over time and limits the number of observations.

Other scholars have done similar studies to add context to these results. Goetz et al. (2012) adds several unique controls to test for the role of social variables in their regression and shifts to a Poisson distribution in its study of the SPLC's 2008 dataset. The authors argue that counties with one hate group are not equally different from counties with two hate groups or zero hate groups. As such, they prefer to use a Poisson, which captures the differences in a non-linear fashion and may be a more accurate tool for analysis than an OLS analysis or a linear probability model (LPM). While the indicator variable in a LPM erases difference between counties with only one hate group versus counties with many, a Poisson distribution can better study their hypothesized non-linear relationship of the number of hate groups in a county (Goetz et al. 2012, 384). They test these data using both a logit and Poisson analysis, with the Poisson analysis using either only variables tested in Jefferson and Pryor (1999) or including other variables – such as religiosity, income inequality and the number of Walmart stores in that county (Goetz et al. 2012, 387). The authors use both income inequality and the number of Walmart stores in an area as variables which proxy for social and economic disruption, which they find increase the likelihood of a hate group being present in a given county. Religiosity, specifically the number of individuals subscribing to the beliefs of certain denominations and religions, serves as one of several variables which proxy for social capital in an area. They argue that counties with more members of religions which are "outward looking," (doing more outreach in the broader community than other religions) such as Catholicism and Mainline Protestantism, would be more likely to display less hate group presence (Goetz et al. 2012, 382). In contrast, counties with more adherents to religions which were "inward looking," specifically evangelical Protestantism, would theoretically see a greater hate group presence (Goetz et al. 2012, 382). However, religious attendance overall might be indicative of higher social capital, which could lower the presence of hate groups (Goetz et al. 2012, 382-383). Goetz et al. (2012) directly contrast their expanded Poisson results with Jefferson and Pryor's 1999 logit results. While Goetz et al. (2012)

find similar results using a logit model like Jefferson and Pryor, their expanded Poisson model sees no significance of the Confederacy when using 2008 data, while variables of economic and social importance become more statistically and economically significant. In addition, while Jefferson and Pryor (1999) found divorce rates to be statistically insignificant in their regression, Goetz et al. (2012) found that the divorce rate was highly correlated with the number of hate groups, even when using the same binary logit methodology of Jefferson and Pryor (1999) (Jefferson and Pryor 1999, 392; Goetz et al. 2012, 387). These differing results, particularly regarding the Confederacy and divorce, suggest the importance of changes over time in the significance of these correlations.

Durso and Jacobs (2013) approach the issue from a sociological perspective, noting that most sociologists had only taken a qualitative approach to studying hate groups (specifically white supremist groups). They analyzed a seven-year period on the state-level and largely only engaged with sociological research on the topic, ignoring some economic analysis which already existed at the time. They defined their independent variables of focus “racial threat” variables – specifically lynchings, the presence of other racist groups, and crime levels. Despite only using a sample of 350 (7 pooled years across all 50 states), their negative binomial count procedure found statistically significant results across their racial threat variables – namely measures of white backlash against other racial groups and a crime measure to see how whites perceive their community to be in danger (Durso and Jacobs 2013, 128 and 134). Their research also found that the increase in hate groups correlated with an increase in the Black population share had a non-linear form with regards to the predicted number of hate groups – peaking at a certain level and declining afterwards (Durso and Jacobs 2013, 130). Their choice of methodology, in combination with other articles, demonstrates that analysis using indicator variables, the number of groups (pooled), and the Poisson distribution have all been used to analyze hate groups.

DiLorenzo (2021) also takes a sociological approach to his panel analysis of hate groups using the SPLC dataset. His primary inquiry questions whether trade related adjustments (domestic job losses caused by globalization) impacted the number of hate groups in the SPLC dataset or hate crimes on the county-level. While DiLorenzo (2021) does use a panel method to analyze the data from 2000-2017, there are potential drawbacks to the data sources he chose to use in his analysis (DiLorenzo 2021, 776-777). He controls for “nighttime luminosity” as a proxy for economic activity, rather than county-level data on unemployment or population which most literature uses. In order to use these data, he carried forward previous results into years with missing values (DiLorenzo 2021, 777). Despite these limitations, he does find that trade related layoffs are a significant predictor of the number of hate groups in an area, especially when interacted with a change in white population. He posits that the pathway to some of these hate groups comes from views of economic racial threat – particularly against Asian and Hispanic groups (DiLorenzo 2021, 782). These results suggest an increased cultural and economic role in the creation and maintenance of hate groups.

To the best of my knowledge, these studies about hate groups have not engaged with literature about deaths of despair. Case and Deaton are largely responsible for the discovery of the national trends in deaths of despair, which they classify as deaths caused by suicide, alcohol, or drugs. Their research over the last decade established that these deaths are generally on the rise among less educated, white non-Hispanic individuals in the United States in the 21st century (Case and Deaton 2017, 1). This increase in death stands in sharp contrast to the general decline in mortality that other groups in the US experienced at this time (Case and Deaton 2017, 5). In their 2017 writing which responds to criticism of their 2015 paper, Case and Deaton noted how age-adjusted mortality (which adjusts the number of deaths in an area relative to the age of its population) are a better way to measure these trends compared to other mortality available (Case and Deaton 2017, 4). They argue in the 2017 addition that income inequality likely does not drive these deaths, as trends in income do not match with trends in deaths of despair across different groups of individuals (Case and Deaton 2017, 14). Instead, Case and Deaton claim that "more likely causes are various slowly moving social trends" or different racial and ethnic groups interpreting changes in income differently (Case and Deaton 2017, 16).

In her senior honors thesis, Boyd (2022) works to connect deaths of despair with a phenomenon which causes social disruption – namely fracking (Boyd 2022, 1). In this model, even though fracking has positive economic benefits for certain workers in the area, the disruption caused by population change and gender imbalance creates a boomtown social disruption (Boyd 2022, 1-2). Her county-level differences in difference (and triple difference in difference) models found that fracking and deaths of despair were positively correlated, despite the increase in income which fracking would presumably bring for individuals (Boyd 2022, 23). Her study illustrates the possible use of deaths of despair as a proxy for social disruptions which are not clearly correlated with other commonly tested variable changes in an area.

Bazzi et al. (2022) examines how the movement of white southerners out of the Deep South throughout the 20th and 21st century made electoral coalitions on the far right viable nationwide (Bazzi et al. 2022, 1). These migrants brought their political beliefs, religion, and cultural products with them when they moved outside of the south in numbers that exceeded the out migration of Black Americans during the Great Migration (Bazzi et al. 2022, 4 and 30). Furthermore, while out-migration of African Americans has declined in recent decades, out-migration of white southerners has only increased – though more Black southerners live outside of the south on a percentage basis (Bazzi et al. 2022, 30). Their county-level shift-share analysis found that migration of white southerners in decades past had a statistically significant impact on both the racial animus expressed in a county, and right-wing political support currently found there (Bazzi et al. 2022, 3 and 18).

III. Theory and Framework

Hate groups have been frequently discussed in sociological frameworks and studied on both qualitative and quantitative levels. Far right and white supremacist groups, which form the vast majority of the SPLC dataset, are hypothesized to form in the US context when "these supremacists claim whites are losing their status as the favored race" (Durso and Jacobs 2013, 128). The pathways for the perception of racial threat can come from multiple sources. Historically in the United States, anxiety around race has been dominated by white fears about Blacks. Fears about racial replacement and Black crime have been a constant undercurrent of white American politics and its "antagonistic" racial relations (Durso and Jacobs 2013, 129). These fears often intersect with economic concerns, but economic concerns are not the entire rationale for the racial threat fears. With the rise in globalization and a more pluralistic society in recent decades, hate against other groups, such as Asians, has intensified from whites as well. Hate towards these groups of people is also connected to ideas about replacement perception of decreased economic opportunity for whites (DiLorenzo 2021, 771-774; Goetz et al. 2012, 379-380).

On the other hand, social movements rely on some amount of organization and resources to "create social change" (Durso and Jacobs 2013, 128). Since hate groups also seek to create social change, they too require some organization and resources to operate. A complex relationship therefore exists between the monetary and social resources needed to start, organize, and maintain these organizations (what I term the social change hypothesis) and the perception of deprivation (what I term the threat hypothesis) required to inspire their creation. Theories about religion, such as how strict and exclusive religions (sects) have more fervent members than other churches, may also be at play given the religious nature of some of the studied groups (Iannaccone 1988, 242).

Adding to the complexity, several variables which have been studied in this context may not track linearly. As an example, the presence of hate groups appears to be correlated with an increase in the Black population, but once a minority population reaches a certain point it can more effectively resist hate group activities from entering the public sphere (Durso and Jacobs 2013, 132). Any theory or analysis ought to take into account these non-linear relationships and mixed evidence supporting the significance of certain variables.

The majority of groups measured by the SPLC clearly fit within the racial threat framework. Whether categorized as the “Ku Klux Klan,” “Neo-Nazis,” or “Racist Skinheads” by the SPLC, these groups largely share a racist worldview to some extent. However, the SPLC tracks multiple hate group ideologies, not all of whom map onto the racial threat discourse. These ideologies include “general hate” groups, anti-LGBT groups, and extremist religious organizations. While the latter two types of groups certainly may share some overlap with white supremacists, the broader idea of hate, as opposed to only white supremacy, deserves theoretical consideration of its own. Some of these ideologies likely arise from similar fears about threat to the dominant socio-economic group. If some white people view wealth held by Black people as a threat to white privilege, so too might some white people view non-Christians or LGBTQ people as a threat. However, this hatred might also come from religious fervor rather than racial or economic insecurity – many of the listed anti-LGBTQ organizations are churches in the vein of the Westboro Baptist Church. In addition, the presence of Black Israelite groups, like the Israelite School of Universal Practical Knowledge, complicates the racial threat framework. These groups led by marginalized populations subscribe to anti-Semitic tropes and believe white people are inherently evil and destined to be killed or enslaved (Southern Poverty Law Center 2022). Of course, the racial threat frameworks for white supremacists do not map onto these kinds of organizations. While these groups are less prominent in the overall dataset, unexpected values could arise from some impact these groups have.

Though deaths of despair have not been studied in connection with hate groups, other factors, such as social capital, economic inequality and divorce rates, have been considered (Goetz et al. 2012, 380). However, all of these variables have theoretically mixed impacts on the number of hate groups. For example, greater social capital could make someone happier and less likely to join a hate group, but it could also make exclusion of "out" groups easier, thus encouraging hate groups (Ibid). Similarly, inequality could bring Black and white workers together in solidarity against those with more resources, or the anger from economic inequality could be displaced onto Black workers. The impact of a variable could also change over time – perhaps inequality created hate prior to an event like the 2009 financial crisis but decreased hate towards racial groups afterwards. Having been historically targeted by hate groups, as Catholics once were, could have a negative impact, no impact, or a positive impact on making certain identities more likely to create, join or maintain hate groups.

Despite these complexities, I hypothesize that deaths of despair will positively correlate with the presence of hate groups. In other words, as deaths of despair increase, I expect that the number of hate groups will increase as well. Scholarly literature has not reached a consensus as to whether hate groups arise in environments with an abundance of social capital, not enough of it, or some non-linear form. This hypothesis prediction relies more so on the threat hypothesis as opposed to the social change hypothesis. In addition, if we assume similarities between sects and hate groups, prior theory has hypothesized that people with lower "secular" prospects would be more attracted to these kinds of groups, supporting the threat hypothesis more broadly (Iannaccone 1988, 260).

IV. Data

I use data on hate groups from the Southern Poverty Law Center's "Hate Map," which records the name, ideology, year, and locality of hate groups. This dataset has some weaknesses. As two examples, membership size was not measured in the dataset, and the ideology variable is vaguely defined for certain groups, such as Black Israelites. As such, the strength of these groups cannot be measured (only their presence) and outlier groups cannot easily be excluded from the dataset. However, the scholarly use of the SPLC Hate Map in prior research reinforces this paper's choice to use this dataset.

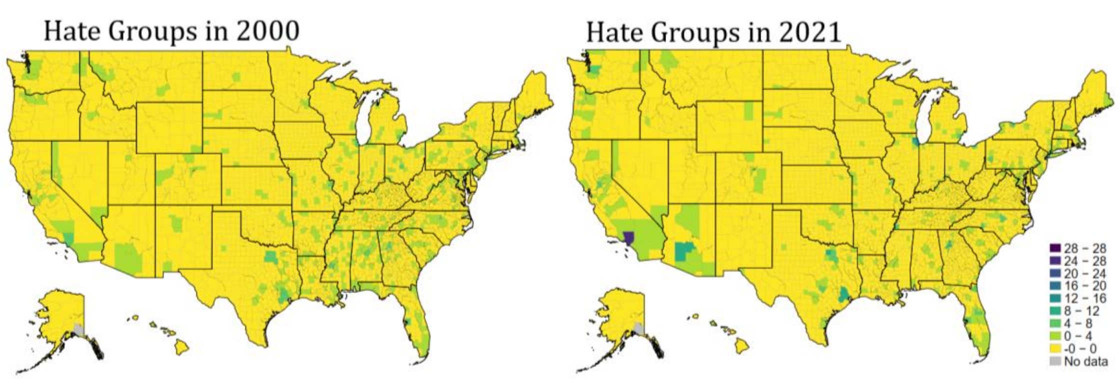
The SPLC defines hate groups as "an organization or collection of individuals that… has beliefs or practices that attack or malign an entire class of people, typically for their immutable characteristics. An organization does not need to have engaged in criminal conduct or have followed their speech with actual unlawful action to be labeled a hate group" (Southern Poverty Law Center 2022). Groups that the SPLC listed which had no county-level location or had vague geographic definitions, such as "upstate," were dropped from the dataset. I merged these data to match with information from Michael Haines' publication of the 2000 City Data Book. I also used a list of Census Designated Places ("representing closely settled, unincorporated communities that are locally recognized and identified by name") published by the Census for the year 2000 get the FIPS code for counties in the dataset (US Census Bureau). I manually entered county locations for data whose CDPs were created more recently. The modified dataset treats cities located in multiple counties as being present in all of those counties for the specific year for the regression. As such, the number of observed hate groups is larger than the number of hate groups present, given that a single group can be split between counties.

Data on deaths of despair comes from the CDC Wonder database. The CDC suppresses data with low count values in order to protect individual identity. As such, exclusively extracting deaths of despair from this database results in about half of all county-level data being suppressed or otherwise unusable. Instead, total age-adjusted mortality for white non-Hispanics ages 35-54, which Case and Deaton argue has increased due to deaths of despair, were used as a proxy. While these deaths are likely indicative of long-term welfare declines, these data have not been time adjusted for the purposes of this study. Annual data on county-level unemployment comes from the Bureau of Labor Statistics via the USDA's Economic Research Service website. Annual population, racial demographics, Hispanic identification, and gender disparity for the county-level comes from the SEER database. County-level education data comes from the US Census Bureau, via the USDA's Economic Research Service. County-level information about religious identification comes from the U.S. Religion Census: Religious Congregations and Membership Study for 2010. Several other variables, such as federal funding and percent population change in past decades, were found in Michael Haines' dataset.

V. Descriptive Statistics

The long-term nature of the dataset provides insights that other papers which use the SPLC dataset have not picked up. One trend is a broader move over time away from the Deep South (ie. Alabama and Mississippi) for hate groups over the past two decades. A concurrent trend has been the concentration of hate groups in certain counties. For example, in 2000 no county had more than 8 observed hate groups. Until 2010, no county had more than 15 hate groups present in it at one time. However, 2021 (the most recent year of data) saw as many as 26 hate groups in one county. This trend of increased concentration continues in other later years – 2019 saw a maximum concentration of 28. Figure One illustrates both of these trends, with relative increases in density and decrease in hate groups distribution in Southern counties clearly visible.

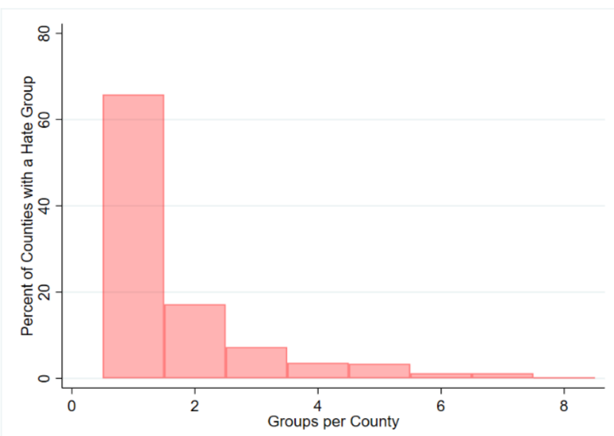
Figure One: Hate Groups per County in 2000 and 2021



This concentration has had meaningful consequences on how hate groups are distributed throughout the country. In the earlier years of the dataset, the vast majority of hate groups are the only one in their county. By the latter half of the dataset however, counties have much more hate groups on average. Figure Two demonstrates this shift by showing how many counties had a certain number of hate groups present in them in different years. This figure demonstrates that more counties have more hate groups and fewer countries have only one hate group in them. This figure also shows how the increase in concentration of hate groups affects the shape of the hate group distribution as a whole. Figure Three, on the next page, shows the number of hate groups observed per year before and after data changes and illustrates that changes to the dataset made for the sake of analysis have largely not affected the shape of the distribution. Pooling the data over different periods of time should minimize any disruption from necessary data changes. The number of groups recorded in a given year varies from the broader trends, meaning a lack of long-term change may exist in this case.

Figure Two: Hate Group Density Distribution

Hate Group Density in 2000



Hate Group Density in 2021

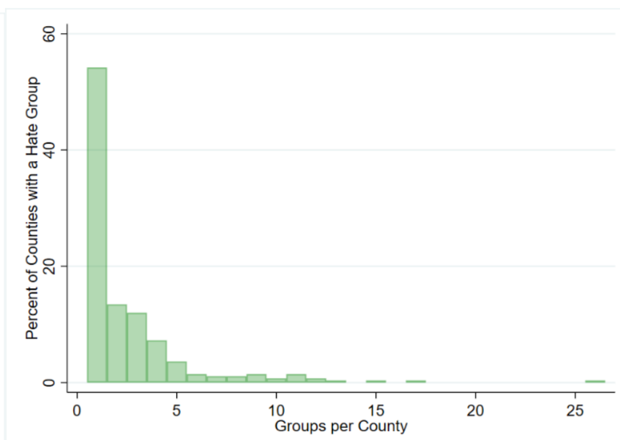
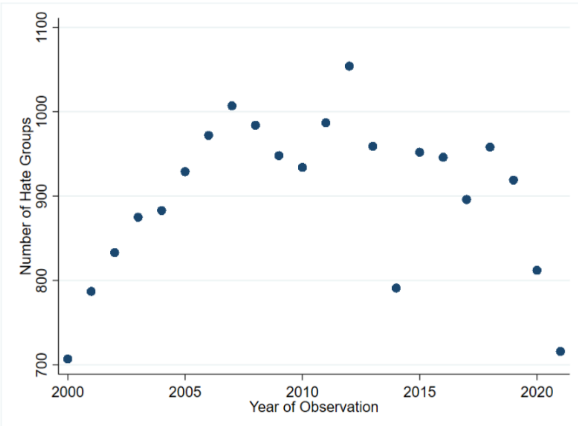


Figure Three: Number of Hate Groups Recorded Yearly – Before and After Modification

Number of Groups After Data Changes **Number of Groups Before Data Changes**



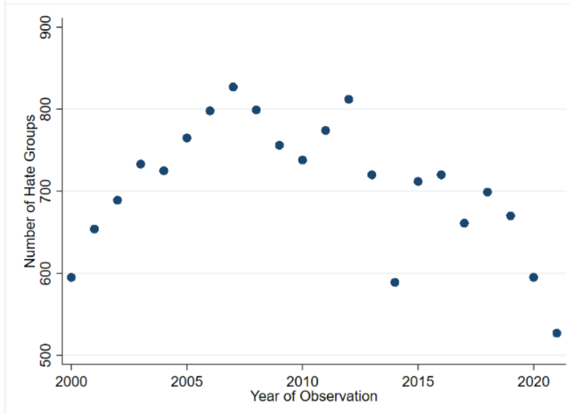


Table One shows the summary statistics for the tested variables when weighted by population or just on the county-level. Data which has not been weighted by population has been effectively weighted by county (one county has one observation) meaning that states with more counties would generally be overrepresented (such as Virginia's independent cities).

In addition to these listed variables, counties also had an indicator variable assigned to them regarding the degree to which they were urban or rural, provided by the USDA and included in the Haines dataset. All displayed regressions use this indicator as one of several control variables. Several additional variables, such as the gender ratio in a county, the presence of slavery in a state as of 1861, Hispanic population squared and the deaths of despair proxy squared were tested. However, these variables were dropped from the final regressions either because they were insignificant economically and empirically, or because of other compounding factors discussed in the results section.

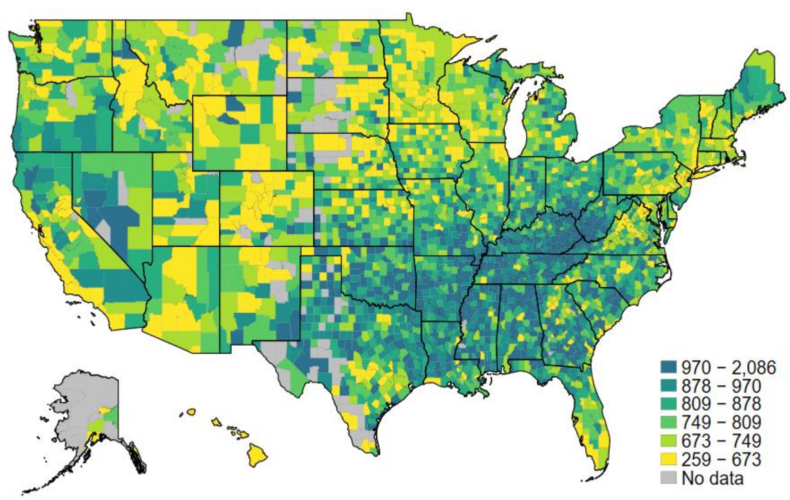
Table One: Means and Standard Deviation of Variables

	Observations	Mean (Unweighted)	S.D. (Unweighted)	Mean (Population weighted)	S.D. (Population weighted)
Hate Group Count	65,785	0.291	1.164	2.639	4.390
Hate Group Indicator	65,785	0.136	0.342	0.546	0.498
Age Adjusted Mortality in observed year (per 1000 in observed year)	63,209	8.503	1.572	7.816	1.259
Log population	65,785	10.26	1.459	12.83	1.617
Log land area	65,785	6.491	0.898	6.619	1.070
Percent Hispanic in observed year	65,785	8.235	13.17	16.11	16.52
Black squared	65,785	305.7	813.2	363.8	701.9
Percent Black in observed year	65,785	9.531	14.66	13.67	13.30
Percent completed high school but not college in 2000	65,785	60.85	6.999	55.93	7.583
Percent completed college in 2000	65,785	16.53	7.794	24.52	9.488
Confederate State	65,785	0.365	0.481	0.338	0.473
Annual unemployment	65,771	6.037	2.685	6.082	2.532
Evangelical rate 2010 (per 1000 in observed year)	65,785	231.4	163.1	161.7	120.3
Catholic rate in 2010 (per 1000 in observed year)	65,785	123.8	135.0	191.4	132.0
Muslim rate in 2010 (per 1000 in observed year)	65,785	2.261	10.58	8.472	12.14
Violent crimes in 1999 (per 1,000 in observed year)	56,398	2.608	2.623	4.558	4.055
Percent population Change, 1990-2000	65,512	11.14	16.05	16.42	17.20
Percent Male in Observed Year	65,785	49.93	2.185	49.17	1.253

However, weighting by population also drastically changes the data in a way which is not conducive to interpretation or geographic study. Given that the data were observed on the county-level, and no other works had seen fit to weight their results by county population, population weighted results thus are not included in the broader analysis.

Just as in the case of hate group presence, age-adjusted mortality also has significant variation on the county-level. Figure Four shows the age-adjusted mortality per 1,000 people in each county in 2019. This figure appears to confirm the trends discussed by Case and Deaton, as the highest death rates appear in de-industrialized, Appalachian, or Southern counties with overrepresentation of less educated whites. This figure also supports the paper's use of age-adjusted mortality as a proxy for deaths of despair. Given that counties with no age-adjusted mortality are dropped from the analysis, this figure also illustrates that despite this, the data used in the analysis still covers the vast majority of the country in both population and area. However, given the impact of the COVID-19 Pandemic on deaths in the United States and certain data limitations, only SPLC data from 2019 and prior was used in the analysis.

Figure Four: Age-adjusted Mortality by County



VI. Empirical Strategy

This paper uses both a Linear Probability Model and Poisson regressions. An LPM is an OLS indicator regression which uses a binary indicator variable to determine whether a county had a hate group in a certain year. For example, two counties – one with three hate groups and one with one hate group in a particular year – would both have indicators equal to 1. On the other hand, the Poisson regression allows more nuanced analysis using probability. Rather than a dummy variable, the Poisson takes the log of the number of hate groups, creating a non-linear line of estimation. A simplified equation for the Poisson and LPM models can be seen below in Equations One and Two. While an OLS analysis using a count variable was considered and briefly tested, that analysis provided an oversized importance to counties with more than one hate group when the vast majority of counties have no hate groups present at any given time.

$$\boldsymbol{H_{ct}} = \boldsymbol{\beta}_0 + X_c{}'\Gamma + Y_{ct}{}'\phi + Z_s{}'\varphi + \epsilon \qquad \textbf{(1)}$$

In this equation, *H* is an indicator as to whether county *c* has a hate group in year *t*. *s* is state, *X* includes variables which occur on the county-level but do not vary over time (such as education as observed in one period or land area), *Y* includes variables which occur on the county and year level (such as deaths each year or population each year), *Z* includes state-level fixed effects (such as whether a state was in the Confederacy) and ϵ is the error term. A one unit increase in *X* would be correlated with a Γ change in the indicator for whether or not a county has a hate group present.

$$\boldsymbol{log}(\boldsymbol{H_{ct}}) = \boldsymbol{\beta}_0 + X_c{}'\Gamma + Y_{ct}{}'\phi + Z_s{}'\varphi + \epsilon \qquad \textbf{(2)}$$

In this equation, *H* is the number of hate groups in county *c* in year *t*. *s* is state, *X* includes variables which occur on the county-level but do not vary over time (such as education as observed in one period or land area), *Y* includes variables which occur on the county and year level (such as deaths each year or population each year), *Z* includes state-level fixed effects (such as whether a state was in the Confederacy) and ϵ is the error term. A one unit increase in X would be correlated with a $(e^{\Gamma} - 1) \times 100$ *percent* change in the number of hate groups and so on (Choueiry 2021).

In addition to exploring the correlation between deaths of despair and hate groups, this analysis also takes some new approaches to analyzing the SPLC data. Prior research has not considered how a certain variables' impacts may change over time. As an example, hate groups may not have responded to the presence of Muslims in a county until after 9/11. Other papers have not had to necessarily consider this change over time, as current literature has largely confined analysis to one year of data. To account for this change, I pooled data into groups of five consecutive years and tested variables in these separate pools in addition to running an analysis using all 20 years of data at once.

VII. Results

Table Two displays the results of the LPM regression on the next page, while the Poisson results are discussed after Table Three. In terms of direction and magnitude, age-adjusted mortality had significant variation depending on the regression type used and the model weights adopted.

Table Two: LPM Model Results, With and Without State Fixed Effects, for 2000-2019

	With Fixed Effects	Without Fixed Effects
Age Adjusted Mortality in observed year (per 1000 in observed year)	0.0031**	0.0056***
	(0.001)	(0.001)
Log population	0.1243***	0.1132***
	(0.002)	(0.002)
Log land area	-0.0065***	0.0063***
	(0.002)	(0.002)
Percent Hispanic in observed year	-0.0009***	-0.0002
	(0.000)	(0.000)
Black squared	-0.0000***	-0.0000***
	(0.000)	(0.000)
Percent Black in observed year	0.0014***	0.0021***
	(0.000)	(0.000)
Percent completed high school but not college in 2000	0.0017***	0.0013***
	(0.000)	(0.000)
Percent completed college in 2000	0.0058***	0.0055***
	(0.000)	(0.000)
Confederate State	N/A	0.0013
		(0.004)
Annual unemployment	0.0023***	0.0006
	(0.001)	(0.001)
Evangelical rate 2010 (per 1000 in observed year)	0.0001***	0.0002***
	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	-0.0000	-0.0000***
	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	0.0003*	0.0002
	(0.000)	(0.000)
Violent crimes in 1999 (per 1,000 in observed year)	0.0129***	0.0130***
	(0.001)	(0.001)
Percent population Change, 1990-2000	-0.0006***	0.0000
	(0.000)	(0.000)
Constant	-1.4524***	-1.3430***
	(0.052)	(0.035)
Observations	51,753	51,753
R-squared	0.287	0.266

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Deaths of despair coefficients were positive and statistically significant in the LPM but not necessarily economically significant. For example, increasing age-adjusted mortality by 1.6 deaths per 1,000, the approximate standard deviation across time and counties, would only be correlated with an increase in the value of the dependent variable, which ranges from zero to one, by 0.00527 in the fixed effects model. In contrast, having 2.5 additional violent crimes in a county per 1,000 people, slightly less than the standard deviation, would be correlated with an increase in the dependent variable by 0.0325. As such, in this model at least, deaths of despair seem to only have a minor correlation with whether a hate group is located in that county or not.[1]

Increasing population in a county had significant, positive coefficients in both the fixed effects and non-fixed effects models. County land area had a negative and statistically significant coefficient with state fixed effects but positive and significant when state fixed effects were used. In contrast to the research of Jefferson and Pryor (1999), a state having been in the Confederacy was not economically or statistically significant, but had a positive coefficient, which does match the results found in their analysis of 1999 data. The Hispanic population in a county as measured in the dataset had a statistically significant small, negative effect on the presence of hate groups which became insignificant and smaller when state fixed effects were not used. With the Hispanic variable however, measurement issues could have arisen regarding undocumented workers, adding complexity to these results. Unemployment, while positive in the state fixed effect regression, similarly lost its significance when state fixed effects were not used. Increased education had positive effects on the presence of hate groups, which matches with prior research that found higher high school graduation rates were correlated with more hate groups in a county. That information could support either the social change or threat hypothesis – either these educated individuals are necessary to form these groups, or the educational inequality, heightened by the presence of more educated people, creates more of a threat for less educated, white workers. While the religious variables were rather small and only occasionally statistically significant, the signs of the coefficients match with what was expected from Goetz et al. (2012) –

[1] Additionally, I ran two quick analyses using only county and year fixed effects, and one with county and year fixed effects with non-colinear controls to see what impact deaths of despair had in this hyper-simplified model. In both runs using the LPM, deaths had a negative, but insignificant, coefficient. This conclusion might suggest that deaths of despair are absorbed not robust to the inclusion of county fixed effects. This could be due to lack of in-county variation of deaths of despair.

positive for evangelicals and negative for Catholics. Muslim population in a county had a small, but statistically significant positive effect. Population change in a county has some small, negative correlation but is largely economically insignificant in this model.[2] While some of these results were robust between LPM and Poisson regressions, several changed in rather drastic manners.

Table Three: Poisson Model Results, With and Without State Fixed Effects, for 2000-2019

	With Fixed Effects	Without Fixed Effects
Age Adjusted Mortality in observed year (per 1000 in observed year)	-0.0735***	-0.0340***
	(0.010)	(0.009)
Log population	0.9158***	0.8768***
	(0.014)	(0.012)
Log land area	-0.1225***	-0.0247**
	(0.015)	(0.012)
Percent Hispanic in observed year	-0.0224***	-0.0130***
	(0.001)	(0.001)
Black squared	-0.0001*	-0.0001**
	(0.000)	(0.000)
Percent Black in observed year	0.0015	0.0078***
	(0.002)	(0.002)
Percent completed high school but not college in 2000	-0.0013	-0.0096***
	(0.003)	(0.002)
Percent completed college in 2000	0.0075***	0.0082***
	(0.002)	(0.002)
Confederate State	N/A	-0.1594***
		(0.021)
Annual unemployment	0.0174***	0.0213***
	(0.004)	(0.003)
Evangelical rate 2010 (per 1000 in observed year)	0.0016***	0.0028***
	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	-0.0007***	-0.0008***
	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	0.0037***	0.0045***
	(0.001)	(0.001)
Violent crimes in 1999 (per 1,000 in observed year)	0.0490***	0.0400***
	(0.003)	(0.002)
Percent population Change, 1990-2000	0.0062***	0.0077***
	(0.001)	(0.000)
Constant	-11.4252***	-10.9945***
	(0.387)	(0.237)
Observations	51,753	51,753

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

In the Poisson models, both with and without state fixed effects, age-adjusted mortality was statistically and negatively economically significant with regards to hate groups. Increasing

[2] I also tested these variables using a two-step regression to incorporate both county fixed effects and the CSA variable (along with other variables which do not vary over time). Only the annual unemployment rate in a county remained significant in this model but does indicate excluding the CSA from certain regressions does not misrepresent its importance.

deaths by one standard deviation in the fixed effects model would decrease the number of hate groups in a county by 12.2% ($(e^{(.0735)} - 1) \times 1.6)$. Population remained positive and significant, while land was positively correlated for poisson models both with and without state fixed effects. The percent of the population which was Hispanic was statistically and economically significant and negative, while the Black population in a county was only positive and statistically significant when state fixed effects were not used. High school education was not statistically significant when state fixed effects were not used, but the coefficient for college completion was positive and significant both with and without fixed effects. When state fixed effects are used, education appears to have a quadratic correlation – a negative coefficient with high school education, but a positive coefficient with college education (as opposed to high school dropouts). The Confederacy indicator variable in the non-state fixed effect run was highly significant and highly negative – the opposite finding of Jefferson and Pryor (1999). Catholic and Evangelical variables remained significant and their expected signs, though the magnitude of their impact greatly increased relative to the LPM model. The Muslim population became highly statistically significant in both models and grew considerably in positive impact on hate groups. Violent crimes and population change both also grew in significance and size of coefficient.

When pooling the results by year, these results become more confusing but also provide more information. Four tables listed in the appendix show the results of these five-year pooled regressions. Broadly speaking, the pooled results line up with the results from all 20 years with some exceptions worth noting. First, age-adjusted mortality was only significant in certain year pools in certain models, and in one Poisson model has a positive coefficient for early years before shifting to negative values in later years. In most models, the share of Muslims in a population also becomes larger and more significant as time goes on. The extent to which these nuances are due to actual change in hate group structure over time versus quirks with the data remains unknown.

Given these different results, age-adjusted mortality must have a complex relationship with the presence or number of hate groups in a county. What explains this discrepancy across models? It might be possible to interpret the data as suggesting deaths of despair make having a hate group in a county slightly more likely but make it significantly less likely a county has multiple hate groups. Assuming that these deaths are an adequate proxy for social disruption as posited in the theory section, this would suggest hate groups arise out of some minor social disruption, but having multiple hate groups requires more social cohesion than disruption.

I tested additional variables in both the LPM and Poisson models which were found to not be significant or whose values did not make sense in these contexts. Though the Black population squared has a theoretical basis in Durso and Jacobs (2013) which was largely born out in these results, squared Hispanic population and squared deaths were not large enough or significant enough to include in these tables, as mentioned in the data section. I also tested gender ratios in a county but given that much of the gender variation in counties comes from small counties having massive predominantly male or female institutions (prisons, schools, military bases, etc.), I dropped gender for the final regressions to prevent confusion and remove confounding variables. However, the variable did turn out to be highly statistically significant in some regressions. As suggested by Boyd's 2022 honor's thesis, along with that of other researchers, gender ought to be examined more in other research given its possible impact on social stability.

VIII. Conclusion

While the age-adjusted mortality results are contradictory on the surface, this study seems to find that these age-adjusted deaths are correlated with the presence of a hate group in a county, but negatively correlated with more than one hate group in a county. These results seem to suggest that while some amount of social disruption increases the likelihood of the presence of hate groups, hate group concentration correlates more with access to resources and organization, or at least being in the presence of greater concentrations of both. On the other hand, the results could suggest that greater inequality in a county, expressed by high levels of educational attainment, could drive the presence of hate groups. Inequality has been examined as a factor in prior papers and was found to be highly significant (Goetz et al. 2012, 387). Of course, the results could also just be spurious correlation – it is possible deaths of despair just pick up effects that are otherwise explained by rurality or urbanity.

However, this research could suggest the discoveries of Case and Deaton could have broad and unexpected societal ramifications, if general age-adjusted mortality is an acceptable proxy for deaths of despair. Furthermore, this analysis supports the conclusions reached by Goetz et al. (2012) and Durso and Jacobs (2013), namely the importance of religion in determining hate group presence and the non-linear shape that Black presence in a county has on the impact of hate groups. These findings also suggest that hate group structure, location and concentration have changed over the past two decades. With regards as to how this research contributes to the broader sociological and economic research on hate groups, the significance of education and mixed evidence regarding deaths of despair suggest that hate groups, at least as determined by the SPLC, are more a product of social cohesion than social disruption.

In addition, this research provides several further avenues for further research by other scholars. Examined variables such as gender, Hispanic population and population change are worth further study in this relatively new field of hate group literature. The intensive cleaning process much of the hate group data had to go through to reach its final stage also suggests the importance of publishing more organized and cleaned hate group data, either by researchers or by the SPLC. However, this study also demonstrates that hate groups are a complex social issue which require immediate government and academic action to understand and hopefully prevent.

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XI. Appendix

Table I: LPM results with state fixed effects, 5 year pools

	(1) 2000-2004	(2) 2005-2009	(3) 2010-2014	(4) 2015-2019
Age Adjusted Mortality in observed year (per 1000 in observed year)	0.0055**	-0.0018	-0.0001	-0.0005
	(0.003)	(0.003)	(0.003)	(0.002)
Log Population	0.1247***	0.1284***	0.1217***	0.1258***
	(0.004)	(0.004)	(0.004)	(0.004)
Log Land	-0.0098**	-0.0048	-0.0023	-0.0130***
	(0.005)	(0.005)	(0.005)	(0.004)
Percent Hispanic in observed year	-0.0005	-0.0012***	-0.0009**	-0.0002
	(0.000)	(0.000)	(0.000)	(0.000)
Black squared	-0.0000**	-0.0000	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)
Percent Black in observed year	0.0007	-0.0000	0.0019***	0.0035***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent completed high school but not college in 2000	0.0018**	0.0011	0.0018**	0.0023***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent completed college in 2000	0.0058***	0.0049***	0.0056***	0.0060***
	(0.001)	(0.001)	(0.001)	(0.001)
Annual unemployment	0.0039*	-0.0019	0.0038***	0.0021
	(0.002)	(0.001)	(0.001)	(0.002)
Evangelical rate 2010 (per 1000 in observed year)	0.0001***	0.0001***	0.0001**	0.0000*
	(0.000)	(0.000)	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	0.0001*	-0.0000	-0.0000	-0.0001**
	(0.000)	(0.000)	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	-0.0000	0.0002	0.0001	0.0009***
	(0.000)	(0.000)	(0.000)	(0.000)
Violent crimes in 1999 (per 1,000 in observed year)	0.0135***	0.0136***	0.0131***	0.0093***
	(0.002)	(0.002)	(0.002)	(0.001)
Percent population Change, 1990-2000	-0.0003	-0.0008***	-0.0006**	-0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.3933***	-1.4299***	-1.4549***	-1.4656***
	(0.109)	(0.110)	(0.103)	(0.096)
Observations	12,951	12,924	12,934	12,944
R-squared	0.293	0.289	0.288	0.317

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table II: LPM results without state fixed effects, 5 year pools

	(1) 2000-2004	(2) 2005-2009	(3) 2010-2014	(4) 2015-2019
Age Adjusted Mortality in observed year (per 1000 in observed year)	0.0054**	0.0018	0.0069***	0.0024
	(0.003)	(0.003)	(0.003)	(0.002)
Log Population	0.1128***	0.1196***	0.1109***	0.1137***
	(0.004)	(0.004)	(0.004)	(0.003)
Log Land	0.0035	0.0090**	0.0054	0.0038
	(0.004)	(0.004)	(0.004)	(0.003)
Percent Hispanic in observed year	-0.0006**	-0.0009***	0.0000	0.0010***
	(0.000)	(0.000)	(0.000)	(0.000)
Black squared	-0.0000***	-0.0000	-0.0000***	-0.0000***
	(0.000)	(0.000)	(0.000)	(0.000)
Percent Black in observed year	0.0028***	0.0007	0.0026***	0.0025***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent completed high school but not college in 2000	0.0010	0.0001	0.0016**	0.0025***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent completed college in 2000	0.0052***	0.0043***	0.0053***	0.0062***
	(0.001)	(0.001)	(0.001)	(0.001)
Confederate State	0.0097	0.0094	-0.0182**	0.0013
	(0.008)	(0.008)	(0.008)	(0.007)
Annual unemployment	0.0026	-0.0017	-0.0006	-0.0024
	(0.002)	(0.001)	(0.001)	(0.002)
Evangelical rate 2010 (per 1000 in observed year)	0.0002***	0.0003***	0.0002***	0.0002***
	(0.000)	(0.000)	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	0.0000	-0.0001*	-0.0000*	-0.0001***
	(0.000)	(0.000)	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	-0.0004*	-0.0001	0.0002	0.0011***
	(0.000)	(0.000)	(0.000)	(0.000)
Violent crimes in 1999 (per 1,000 in observed year)	0.0137***	0.0158***	0.0117***	0.0097***
	(0.001)	(0.001)	(0.001)	(0.001)
Percent population Change, 1990-2000	0.0003	0.0001	0.0002	-0.0005**
	(0.000)	(0.000)	(0.000)	(0.000)
Constant	-1.3159***	-1.2723***	-1.3146***	-1.3972***
	(0.074)	(0.075)	(0.071)	(0.064)
Observations	12,951	12,924	12,934	12,944
R-squared	0.267	0.263	0.258	0.295

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table III: Poisson results with state fixed effects, 5 year pools

	(1) 2000-2004	(2) 2005-2009	(3) 2010-2014
Age Adjusted Mortality in observed year (per 1000 in observed year)	0.0254	-0.0533**	-0.0835***
	(0.022)	(0.022)	(0.025)
Log Population	0.8474***	0.9021***	0.9380***
	(0.028)	(0.026)	(0.028)
Log Land	-0.1483***	-0.1241***	-0.0808***
	(0.031)	(0.029)	(0.030)
Percent Hispanic in observed year	-0.0192***	-0.0261***	-0.0232***
	(0.003)	(0.003)	(0.003)
Black squared	-0.0000	0.0001	-0.0002**
	(0.000)	(0.000)	(0.000)
Percent Black in observed year	0.0025	-0.0055	-0.0019
	(0.004)	(0.004)	(0.004)
Percent completed high school but not college in 2000	-0.0025	-0.0067	0.0092*
	(0.006)	(0.005)	(0.006)
Percent completed college in 2000	0.0173***	0.0027	0.0128***
	(0.005)	(0.004)	(0.005)
Annual unemployment	0.0712***	-0.0044	0.0503***
	(0.014)	(0.007)	(0.010)
Evangelical rate 2010 (per 1000 in observed year)	0.0015***	0.0015***	0.0019***
	(0.000)	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	-0.0002	-0.0005*	-0.0011***
	(0.000)	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	-0.0008	0.0025	0.0061***
	(0.002)	(0.002)	(0.002)
Violent crimes in 1999 (per 1,000 in observed year)	0.0358***	0.0439***	0.0683***
	(0.006)	(0.006)	(0.007)
Percent population Change, 1990-2000	0.0107***	0.0063***	0.0058***
	(0.001)	(0.001)	(0.001)
Constant	-11.1031***	-11.4150***	-13.2925***
	(0.738)	(0.907)	(0.835)
Observations	12,951	12,924	12,934

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note – STATA would not run 2015-2019 regressions with this model due to multicollinearity issues not present in other years.

Table IV: Poisson results without state fixed effects, 5 year pools

	(1) 2000-2004	(2) 2005-2009	(3) 2010-2014	(4) 2015-2019
Age Adjusted Mortality in observed year (per 1000 in observed year)	0.0599***	0.0234	-0.0260	-0.1193***
	(0.020)	(0.019)	(0.021)	(0.021)
Log Population	0.8015***	0.8536***	0.8631***	1.0053***
	(0.025)	(0.024)	(0.025)	(0.027)
Log Land	-0.0335	0.0089	-0.0175	-0.0929***
	(0.025)	(0.023)	(0.024)	(0.025)
Percent Hispanic in observed year	-0.0161***	-0.0155***	-0.0125***	-0.0076***
	(0.002)	(0.002)	(0.002)	(0.002)
Black squared	-0.0001**	-0.0000	-0.0002***	0.0000
	(0.000)	(0.000)	(0.000)	(0.000)
Percent Black in observed year	0.0161***	0.0029	0.0088**	-0.0000
	(0.004)	(0.004)	(0.004)	(0.004)
Percent completed high school but not college in 2000	-0.0063	-0.0138***	-0.0035	0.0080*
	(0.005)	(0.004)	(0.005)	(0.005)
Percent completed college in 2000	0.0174***	0.0064*	0.0139***	0.0195***
	(0.004)	(0.004)	(0.004)	(0.004)
Confederate State	0.0215	-0.0694*	-0.4242***	-0.1034**
	(0.043)	(0.040)	(0.041)	(0.043)
Annual unemployment	0.0924***	0.0053	0.0431***	0.0601***
	(0.012)	(0.007)	(0.008)	(0.015)
Evangelical rate 2010 (per 1000 in observed year)	0.0024***	0.0026***	0.0031***	0.0032***
	(0.000)	(0.000)	(0.000)	(0.000)
Catholic rate in 2010 (per 1000 in observed year)	-0.0001	-0.0005**	-0.0011***	-0.0015***
	(0.000)	(0.000)	(0.000)	(0.000)
Muslim rate in 2010 (per 1000 in observed year)	-0.0007	0.0037***	0.0065***	0.0071***
	(0.002)	(0.001)	(0.001)	(0.001)
Violent crimes in 1999 (per 1,000 in observed year)	0.0251***	0.0372***	0.0509***	0.0431***
	(0.005)	(0.005)	(0.005)	(0.005)
Percent population Change, 1990-2000	0.0112***	0.0083***	0.0072***	0.0036***
	(0.001)	(0.001)	(0.001)	(0.001)
Constant	-11.7737***	-10.9381***	-11.5833***	-12.9445***
	(0.518)	(0.464)	(0.487)	(0.504)
Observations	12,951	12,924	12,934	12,944

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1