

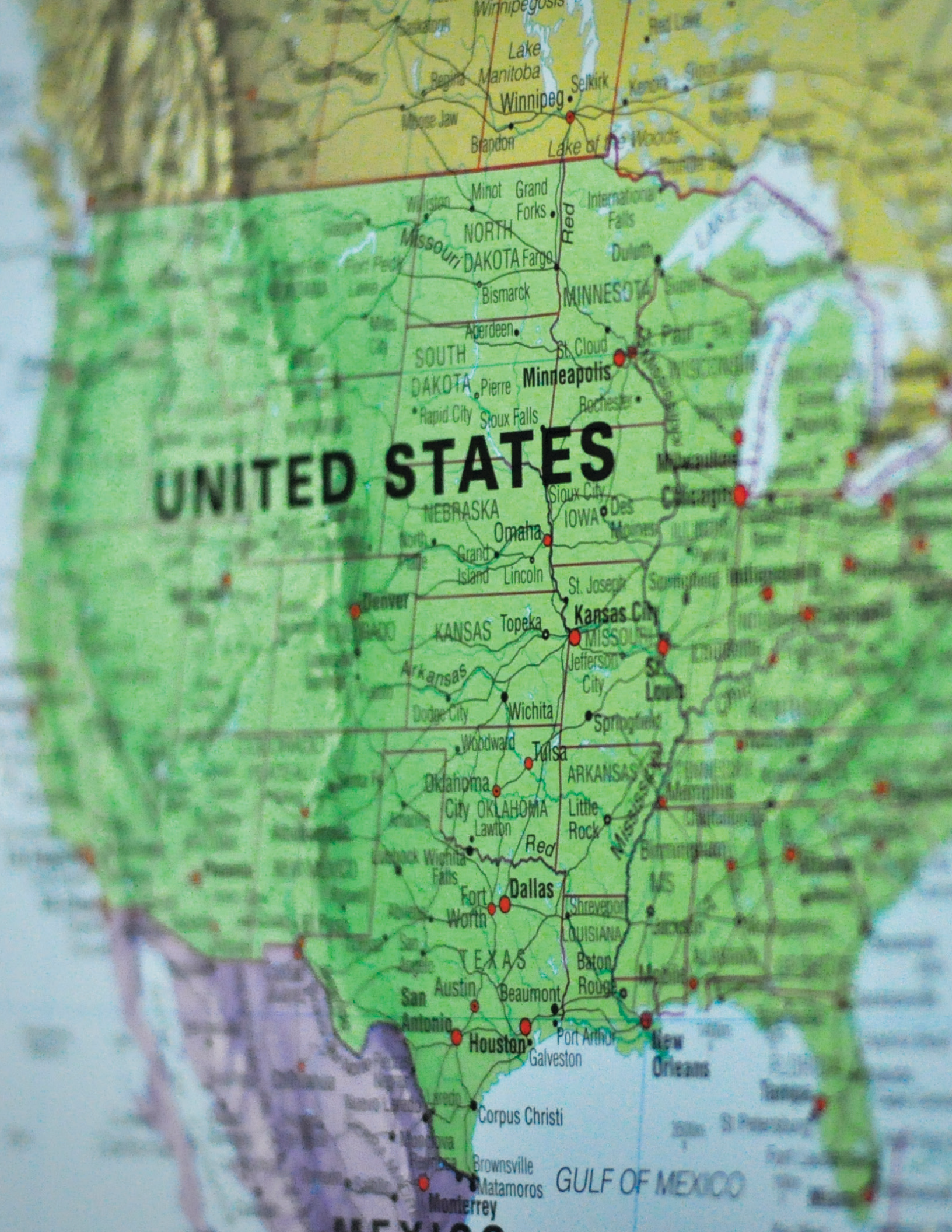


THE STATE OF HATE INDEX

ROBERT TYNES

A BARD CENTER FOR THE
STUDY OF HATE PUBLICATION

UNITED STATES



PREFACE

Kenneth S. Stern

Director, Bard Center for the Study of Hate

The Bard Center for the Study of Hate (BCSH) is honored to support the production and promotion of Robert Tynes's groundbreaking THE STATE OF HATE INDEX.

The demonization and/or dehumanization of others is a larger phenomenon than just how many swastikas are drawn on synagogues or people attacked for who they are perceived to be. Sometimes hate is normative and not expressed viscerally, at times through laws that exclude people from civil rights and other protections based simply on who they are or who they love. Sometimes we see data about the various specific phenomena that reflect hate, but the data are usually incomplete and siloed.

What Tynes directs us to do is think more broadly. What are the various factors in each state that can be quantified to give us information about hate writ large, and the chances people will encounter it?

We hope this landmark study will spur others to replicate this type of approach. One might quibble about which factors are included (or not included), and the relevant weights one data set or another is given. But the larger frame is the major contribution of Tynes's approach—to see hate as a combination of factors operating simultaneously in a defined geographic area.

We also hope that human rights communities, legislators, business and religious leaders, and others in states toward the bottom of this Index will use this study to advocate changes that can improve the lives of their neighbors. Law can be amended or adopted, and practices improved, that can reduce the quantity of hate. Tynes's Index is a guidepost of what changes should be considered.

BCSH thanks GS Humane Corporation for understanding the importance of this project and underwriting it, and Bard colleagues and others who reviewed the text, and helped design and promote it.



THE STATE OF HATE INDEX

Robert Tynes¹, Bard College²

Hate is not the status quo. Whenever hate arises as a motivation for violence, we are witnessing a break in what is normal. The fallout is not simply emotional. The end result can be damage to property, to bodies, and to entire groups of people. The *State of Hate Index (SoHI)* is an initial sketch of the potential for hate-based violence³ in a given region. The goal is to map out where hate, and the possibility of hate-based harm, is more prominent. *SoHI* examines how hate manifests, and is constrained, in the 50 states of the United States, looking at multiple indicators in order to suggest when hate might be more likely to occur.⁴

Think of it as an expansion of Victor Hugo Green's idea for the *Negro Motorist Green Book*. For 30 years, starting in 1936, Green published a guide for African Americans who were traveling across the United States. The book listed motels, restaurants, and gas stations that were friendly to African Americans—places in which they could take refuge from racist whites while driving across America.⁵ Green's guide was similar to the Jewish travel guides of the 1930s that mapped out the more hospitable places to be in the Catskills.⁶ The *State of Hate Index* takes a broader view, pulling back to the state level and providing the general landscape for hate across America.

Discourse in the media and among public opinion leaders often ascribe stereotypical depictions of parts of the country as more racist, or less friendly to Lesbian, Gay, Bisexual, Transgender, Queer/Questioning, and other gender identities (LGBTQ+). The South is often described as racist because of the legacy of slavery. New York has been portrayed as a gay Mecca, due to its annual Gay Pride Parade and the legacy of the Stonewall Uprising. These oversimplifications are deceptive though, providing mostly fear and threat rather than empirical reality. The *State of Hate Index* is hopefully one step toward reality.

The United States includes a wide range of social groups and norms across vast landscapes. Trying to partition off where hate clusters within that terrain is not easy. States, however, are a valid starting point, as we find a combination of social groups (ethnicity, gender, class, etc.) interacting with structured limitations—laws and policies. Driving across the border from Nevada to Idaho means losing significant legal protections if you are LGBTQ+. Political lines on a map do matter when it comes to hate. Sociologists (Bourdieu, Wacquant, and Farage 1994) emphasize how this dynamic is common when human bodies enter and leave different fields of contention. They note that political boundaries create power dynamics and increase threat: “The construction of the state monopoly over physical and symbolic violence is inseparable from the construction of the field of struggles of the monopoly over the advantages attached to this monopoly” (pp. 16–17).⁷

Further, such a construction also determines who counts as human: “The political field is the field par excellence for the exercise of symbolic capital; it is a place where to exist, to be, is perceived.” (p. 192, Bourdieu 2014). For *SoHI*, hate is defined as “the human capacity to define, and then dehumanize or demonize, an ‘other’ . . .” (p. 11, Stern 2004), so that crossing state lines has the potential to humanize or dehumanize, to determine if you exist or not. This is the implication explored by the *Index*, one that groups of people who are discriminated against feel in their bones, while those who have not been persecuted due to ethnicity, gender, class, etc., barely notice, if at all.

Methodology

Gathering data to represent how hate plays out on the ground is not straightforward. Questions such as which vulnerable groups should be accounted for and what are the best measures for representing hate are at the center of the *SoHI*. Ideally one would include as many vulnerable groups as possible, assess which measures are extremely accurate, and then tally the results. This is not, however, the terrain of hate statistics.

One common marker is the U.S. Federal Bureau of Investigation (FBI) statistics on hate crimes by state. The FBI collects yearly data from each state counting hate crimes from vandalism to assault to murder. The accounting is extensive, however, it is based on what states self-report, which means states must relay accurate information and must classify the same crimes as hate crimes. Unfortunately, there is a wide range of variation and underreporting and underclassification is apparent in the data. As a consequence, the *SoHI* does not incorporate FBI hate crime numbers into the Index, but the FBI data will be shown along with the overall rankings.

Setting aside the FBI data, the Index aligned its model with Bourdieu, approaching hate from two angles. First, in line with habitus, data that measured *embodiment*—in actions and groups—was utilized. Second, *structure/field* measures, such as laws and policies, were also incorporated. *SoHI* uses the U.S. state as the level of analysis, as this is where we find the most comprehensive data across all of the U.S. and the most expansive timeframe. Of course, there may be wide variation within those political boundaries: northern Michigan is sociopolitically different than the University of Michigan college town. Yes, Ann Arbor is different than Alpena, but hate groups exist in both cities, and Whiteness is a more salient part of the identity of a Michigander as compared to the identity of a New Yorker.

Embodiment—actions and groups

Embodiment was split into: a) those groups whose actions and identities promote and enact hate (hate groups); and b) those groups whose actions and identities receive hate through violence. Hate Groups data was collected from the Southern Poverty Law Center (SPLC 2020a) and its determination of hate groups by state. SPLC defined hate groups 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” (SPLC 2020b). The measure for this is *Number of Hate Groups*. Some groups that received hate were harder to represent. There are very little reliable state-level statistics that track violence against people who are LGBTQ. This is also true for violence against Asian Americans and Pacific Islanders (AAPI), which lacks accurate tracking also because of underreporting by the community and victims.⁸ The FBI Hate Crimes data does count violence against people who are LGBTQ or AAPI, but it is inaccurate and not comparable from state to state. Because of this, protections for people who are LGBTQ appear in the structural/field measures. There are three groups that had consistent data tracking violence against them (women, people who are Jewish, and people perceived as non-white), and these are the measures used: *Violence Against Women* (Smith et al 2017), *Anti-Semitic Violence* (Anti-Defamation League 2020), and *White Supremacy Violence* (Anti-Defamation League 2020).⁹



Structure/field—laws and policies

Laws and policies can provide protection from hate-based violence, in the very least, by instituting social norms (*nomos*) against violence. They are structural elements that raise the cost for anyone who considers harm against an individual or an organization based on their race/ethnicity, religion, gender, gender identity, and so forth. Laws and policies also create and maintain the narrative necessary to make the norm a more concrete reality.¹⁰ The Index draws on three sets of information. First, Levin and Nakashima (2019) created a dataset tracking the *General Laws and Policies to the Prevention of Hate*. Their data includes discrimination based on age and based on homelessness in addition to race/ethnicity, gender identity, etc. Second, the Human Rights Campaign (2020) monitors state laws regarding issues such as transgender healthcare, adoption for same sex couples, antibullying, and anti-conversion therapy. This measure is *Law and Policies LGBTQ*. Third, Gerney and Parsons (2014) looked at gun and domestic violence laws nationwide, analyzing how states protect women from gun violence perpetrated by domestic partners. Their study tracks laws on gun possession prohibitions related to protection orders, sex crimes, and stalking crimes as well as laws that require the surrender of weapons. Their data in the Index helps represent how serious states are about saving women's lives. This measure is *Guns and Domestic Violence Laws*.

In total there are seven measures in the Index—four for the embodiment category plus three for structure/field category (See Table 1). The time frame spans a decade, from 2010 to 2020, with the most recent and/or accurate dataset being utilized or a collection of yearly datasets being used. The past and more current time reference reveal how the field of hate has manifested into its current form. This does not mean that similar hate-based events are inevitable in the future. It does reveal, however, to what extent a state is primed for future violence. Each measure is of equal weight in the Index, but calculating the measure itself in some cases utilized a weighted system (See Appendix A for details). The measures are not absolute for the state of hate, but together they do create the closest model we have to date for the

TABLE 1: MEASURES BY CATEGORIES

EMBODIMENT	STRUCTURE/FIELD
Number of Hate Groups	General Laws and Policies Relating to the Prevention of Hate
Violence against Women	Laws & Policies LGBTQ
Anti-Semitic Violence	Guns and Domestic Violence Policies
White Supremacy Violence	

potential for violence and dehumanization in a given region in the United States. For each measure, the raw data was recorded state by state. Then, all variable data was converted into a ranking system: 1–51. (District of Columbia was included, because it is a considered a significant territory by the U.S. Census and all the other agencies whose data is included in the Index.) The ranking system allows us to see how states compare to one another. It is a closed universe though, so it only describes how each state does in comparison to the others and not how much of a field of hate exists in that territory. In other words, the 51st rank means that that state has the greatest potential for hate-based violence in the United States. Even at 51st, a state could be “not so bad,” though; just bad when considering the other states. After each measure was converted to a rank, the ranks are added together to generate a composite score. The lowest score translates to the “best” or most hospitable state. For the Index, the lowest composite score is 63 and the highest is 285. The composite scores are ranked and a final scale is the result (1–51).¹¹

State of Hate Index

The top five states where hate is less likely to flourish and lead to violence are: New York, Hawaii, Illinois, California, and Connecticut. The bottom five states where hate is more likely to manifest into violence are: Arkansas, Wyoming, South Dakota, Montana and, lastly, Idaho (See Table 2).

If we look for patterns based on region, we see states from all parts of the country sprinkled throughout the ranking. There is a preponderance of Eastern and Northeastern states at the top, accounting for seven of the first 11 states. The Southern and Western states tend to be in the middle to the bottom of the rankings. There are exceptions, such as Florida and California (See Table 3).

If we compare political parties, Democrats or Republicans, we find a clear polarization with Democrats at the top of the rankings and Republicans filling out towards the bottom (See Table 4). Political party in control by state is based on the analysis of the State and Legislative Partisan Composition conducted by the National Conference of State Legislatures (2020). The overall state control by party was determined by the composition of the legislative party in control plus the governor’s party. The final state control coding also considered the general trend of state party control from 2016–2020.

Taking a more conceptual approach, we can compare the Embodiment rankings with the Structure/Field Rankings. What we find is some correlation between the two categories for some states, such as Hawaii, New York, Connecticut, South Dakota, and Idaho. However, there is a wide difference between the Embodiment rankings and Structure/Field rankings for Michigan, Colorado, Washington, and New Hampshire. (See Table 5 below). This may indicate that the legal and social norms generated in some states lag behind on the ground events. In other words, enforcement of laws and policies may be stronger in New York and lax in Idaho, which is why Embodiment and Structure/Field are more closely aligned. Whereas, in Michigan or Colorado, laws and policies may be strong, but enforcement is not consistent.

TABLE 2: THE STATE OF HATE INDEX

STATE	NUMBER OF HATE GROUPS	VIOLENCE AGAINST WOMEN	ANTI-SEMITIC VIOLENCE	WHITE SUPREMACY VIOLENCE	GENERAL LAWS & POLICIES Relating to the Prevention of Hate	LAWS & POLICIES LGBTQ	GUNS AND DOMESTIC VIOLENCE LAWS	TOTAL	OVERALL RANK
New York	13	19	12	15	2	1	1	63	1
Hawaii	28	10	6	1	10	10	10	75	2
Illinois	14	23	3	16	10	10	4	80	3
California	10	18	15	35	2	1	1	82	4
Connecticut	5	27	26	18	10	1	10	97	5
New Jersey	8	30	20	28	10	1	4	101	6
Maryland	27	36	2	11	2	14	19	111	7
Massachusetts	9	14	32	38	17	1	15	126	8
Florida	29	9	7	10	17	35	25	132	9
Delaware	51	12	21	3	17	14	15	133	10
District of Columbia	21	48	30	26	1	1	8	135	11
Iowa	2	10	46	29	17	21	10	135	11
Minnesota	11	47	27	30	2	14	4	135	11
Nevada	25	41	5	19	10	1	34	135	11
Rhode Island	7	2	31	33	17	14	34	138	15
New Mexico	1	34	41	13	2	14	34	139	16
Pennsylvania	19	27	13	17	39	24	10	149	17
Missouri	37	16	8	8	10	39	34	152	18
Texas	15	25	16	21	17	41	19	154	19
Washington	32	50	19	42	8	1	4	156	20
Kansas	3	39	4	20	29	31	34	160	21
North Carolina	34	5	28	9	39	27	19	161	22
Tennessee	45	21	24	14	17	41	1	163	23
Louisiana	41	1	36	6	17	46	19	166	24
Utah	20	4	44	48	2	23	25	166	24
Colorado	35	22	33	41	17	10	10	168	26
Ohio	23	24	9	24	39	31	25	175	27
Wisconsin	16	19	40	31	29	24	19	178	28
Oregon	30	51	17	37	10	1	34	180	29
Vermont	4	35	38	51	8	10	34	180	29
Michigan	24	33	18	12	34	28	34	183	31
West Virginia	17	6	42	44	34	35	8	186	32
Virginia	42	17	11	25	39	22	34	190	33
Georgia	36	7	22	4	47	41	34	191	34
Arizona	18	45	14	27	34	39	19	196	35
Oklahoma	12	14	37	40	29	46	25	203	36
Maine	33	43	29	45	17	14	25	206	37
Kentucky	22	39	10	39	29	35	34	208	38
Mississippi	40	27	25	2	34	46	34	208	38
Alabama	44	13	35	5	39	46	34	216	40
Indiana	31	30	34	22	47	31	25	220	41
North Dakota	38	3	51	34	34	35	25	220	41
Alaska	46	49	1	32	29	30	34	221	43
Nebraska	39	25	48	36	17	41	15	221	43
New Hampshire	49	38	43	47	17	14	15	223	45
South Carolina	26	42	23	7	47	46	34	225	46
Arkansas	43	30	45	23	47	28	34	250	47
Wyoming	6	37	39	49	47	41	34	253	48
South Dakota	50	8	49	46	39	46	25	263	49
Montana	48	46	50	50	39	24	25	282	50
Idaho	47	44	47	43	39	31	34	285	51

TABLE 3: STATE RANKINGS WITH REGION

STATE	REGION	OVERALL RANK
New York	NE	1
Hawaii	FW	2
Illinois	MW	3
California	W	4
Connecticut	NE	5
New Jersey	NE	6
Maryland	E	7
Massachusetts	NE	8
Florida	S	9
Delaware	E	10
District of Columbia	E	11
Iowa	MW	11
Minnesota	MW	11
Nevada	SW	11
Rhode Island	E	15
New Mexico	SW	16
Pennsylvania	NE	17
Missouri	S	18
Texas	SW	19
Washington	NW	20
Kansas	MW	21
North Carolina	S	22
Tennessee	S	23
Louisiana	S	24
Utah	W	24
Colorado	W	26
Ohio	MW	27
Wisconsin	MW	28
Oregon	NW	29
Vermont	NE	29
Michigan	MW	31
West Virginia	S	32
Virginia	S	33
Georgia	S	34
Arizona	SW	35
Oklahoma	W	36
Maine	NE	37
Kentucky	S	38
Mississippi	S	38
Alabama	S	40
Indiana	MW	41
North Dakota	W	41
Alaska	FN	43
Nebraska	W	43
New Hampshire	NE	45
South Carolina	S	46
Arkansas	S	47
Wyoming	S	48
South Dakota	W	49
Montana	W	50
Idaho	W	51

TABLE 4: STATE RANKINGS WITH POLITICAL PARTY

STATE	STATE AND LEGISLATIVE PARTISAN COMPOSITION	OVERALL RANK
New York	DEMOCRAT	1
Hawaii	DEMOCRAT	2
Illinois	DEMOCRAT	3
California	DEMOCRAT	4
Connecticut	DEMOCRAT	5
New Jersey	DEMOCRAT	6
Maryland	SPLIT	7
Massachusetts	SPLIT	8
Florida	REPUBLICAN	9
Delaware	DEMOCRAT	10
Iowa	REPUBLICAN	11
Minnesota	SPLIT	11
District of Columbia	DEMOCRAT	11
Nevada	DEMOCRAT	11
Rhode Island	DEMOCRAT	15
New Mexico	DEMOCRAT	16
Pennsylvania	SPLIT	17
Missouri	REPUBLICAN	18
Texas	REPUBLICAN	19
Washington	DEMOCRAT	20
Kansas	SPLIT	21
North Carolina	SPLIT	22
Tennessee	REPUBLICAN	23
Louisiana	SPLIT	24
Utah	REPUBLICAN	24
Colorado	DEMOCRAT	26
Ohio	REPUBLICAN	27
Wisconsin	SPLIT	28
Vermont	SPLIT	29
Oregon	DEMOCRAT	29
Michigan	SPLIT	31
West Virginia	REPUBLICAN	32
Virginia	DEMOCRAT	33
Georgia	REPUBLICAN	34
Arizona	REPUBLICAN	35
Oklahoma	REPUBLICAN	36
Maine	DEMOCRAT	37
Kentucky	SPLIT	38
Mississippi	REPUBLICAN	38
Alabama	REPUBLICAN	40
Indiana	REPUBLICAN	41
North Dakota	REPUBLICAN	41
Alaska	REPUBLICAN	43
Nebraska	REPUBLICAN	43
New Hampshire	SPLIT	45
South Carolina	REPUBLICAN	46
Arkansas	REPUBLICAN	47
Wyoming	REPUBLICAN	48
South Dakota	REPUBLICAN	49
Montana	SPLIT	50
Idaho	REPUBLICAN	51

TABLE 5: EMBODIMENT AND STRUCTURE/FIELD CATEGORIES COMPARED

STATE	EMBODIMENT ONLY RANK	STRUCTURE/FIELD ONLY RANK
Hawaii	1	9
Florida	2	27
Illinois	3	8
New York	4	1
Kansas	5	36
Georgia	6	49
Missouri	6	31
Rhode Island	8	23
Connecticut	9	7
Maryland	9	11
North Carolina	9	32
Pennsylvania	9	25
Texas	13	27
California	14	1
Ohio	15	38
Louisiana	16	30
New Jersey	17	5
Delaware	18	15
Iowa	18	17
Michigan	18	40
New Mexico	21	18
Nevada	22	13
Massachusetts	23	10
Mississippi	24	47
Virginia	25	38
Alabama	26	48
South Carolina	27	51
Oklahoma	28	42
Arizona	29	34
Tennessee	29	22
Wisconsin	31	24
West Virginia	32	27
Kentucky	33	41
Minnesota	34	6
Utah	35	18
Indiana	36	43
District of Columbia	37	3
North Dakota	38	36
Alaska	39	35
Vermont	39	20
Colorado	41	12
Wyoming	41	49
Oregon	43	13
Arkansas	44	45
Washington	45	4
Nebraska	46	25
Maine	47	21
South Dakota	48	46
New Hampshire	49	15
Idaho	50	44
Montana	51	33



Some of the Dynamics of Hate-based Violence

The *SoHI* is a starting point for understanding where hate-based violence is generated (or not). If we accept the Index as a baseline about hate, we can then turn to an exploration of correlations and explanations for why hate happens in certain regions. The point here is not to make predictions, but rather to extend what is revealed from *SoHI* to generate ideas for further research.

Social groups—families, religious collectives, states, etc.—coordinate and cooperate on a regular basis in order to satisfy their wants, needs, and desires. These interactions, however, can become contentious, and may or may not lead to violence. Most of the time, contention in social groups does not lead to violence. In fact, it is more commonly diffused and remedied. Sometimes contention does rise to the level of conflict; and when hate enters the social field of discontent, the results can be disastrous.

Following Gurr, an essential flip from internal discontent to external discontent begins with relative deprivation. This is a reflexive action wherein an individual/social group views the loss or denial of a resource in relationship to another individual/social group. The individual/social group perceives the loss or denial of a resource as being the fault of the other—you, she, he, we are being deprived relative to the other. At this point, the Us/Them dichotomy, so essential to the development of hate, manifests. When relative deprivation is activated, then frustration becomes more salient in the social psychology of the group. Sometimes this frustration is instrumentalized into aggression, as a method for acquiring the resource perceived as lost or denied because of the other. Further instrumentalization can lead to hate-based violence against a dehumanized THEM. Whether or not the violence can achieve the goal is inconsequential. The most important point is that the group perceives violence as the *only* method for achieving their goal.

The pathway to hate-based violence is not inevitable. Group cohesion through political violence necessitates both internal and external forces. Internally, some members of the group may band



together and call for violence, at which point they must persuade the rest of the group that violence is the most rational course of action. This is a “ground up” type of mobilization that Kaufman (2001) describes in his work on ethnic conflict. A group can also be mobilized by charismatic individuals who are adept at manipulating the discourse surrounding group discontent.¹² These elites are political entrepreneurs who manipulate certain facets of social groups’ webs of significance (Geertz 1977), signs and symbols that can be essentialized and concretized as the only, inescapable, reality.

The model outlined above presents some of the core dynamics involved in the generation of hate-based violence. With the *SoHI* we can test the model, building on the work of others. Yitzhaki (1979) and Panning (1983) link income inequality as measured by the Gini Coefficient, to relative deprivation. Further, Levin and McDevitt (1993) find a relationship between economic deprivation and hate-based violence; and Craig (2002) discusses how poverty and employment might spark greater hate. Other social scientists have found a connection between urbanization and hate crimes. Ilganski and Levin (2004) analyze the dynamics of greater heterogeneity in urban areas versus greater homogeneity in rural areas. They find that in rural areas there can be less diversity, which leads to a greater likelihood of polarization and the solidifying of an Us versus Them frame of mind. The result is more extremism and racism in rural regions. Wilson and Ruback (2003) find that hate crimes are higher in rural counties of Pennsylvania when compared to urban counties. They note, however, that it could be that hate crimes are more likely to be classified as such in rural areas, a problem perhaps of the unreliability of hate crime reporting.

Taking these studies as points for exploration, we can pull out four independent variables: income inequality, poverty, unemployment, and urbanization. *Income inequality* is measured by the Gini Index for each state (U.S. Census Bureau 2020a). *Poverty* is measured by the poverty level for each state (U.S. Census Bureau 2020b). *Unemployment* is measured by the unemployment rate for each state (U.S. Bureau of Labor Statistics 2020). *Urbanization* is measured by the urban percentage of the population for each state (U.S. Census Bureau 2020c). *Hate crimes*, as a ratio of the number of crimes over the population



of the state (FBI 2016, 2017, 2018), is also included as a fifth variable for comparison.¹³ The dependent variable is the *SoHI* rank as measured by the total score (range: 63-285). Conducting a linear regression analysis to see if there were any correlations, we find two significant variables. Both Urbanization and Income Inequality strongly correlate with the Overall Rankings for hate in a state (See Table 5).

Urbanization exhibits an extremely strong correlation (>99.99%), and Income Inequality a significant correlation (>95%). The findings show that the greater the urbanization, the lesser the likelihood of hate in the state. This supports the work of Ilganski and Levin (2004) and Wilson and Ruback (2003) and the notion that the greater the heterogeneity of a population, the less likelihood of conflict based on socially constructed differences. Basically, when more racially/ethnically/gender-defined groups are in daily conflict, the notion of difference and an Us/Them relationship is less salient. For Income Inequality (as measured by the Gini Coefficient) the correlation is negative in direction, which means for states, as income inequality increases, hate *decreases*. While this may run counter to theories about relative deprivation, it could be that what we see is a greater sense of competitiveness when incomes are more equal, especially in rural areas where the only exposure to upper classes may come through the media. In the cities, economic inequality can be overwhelming large; however, people from all classes intermingle every day, making economic frustration more of an immediate reality, rather than a mediated imaginary, and, similar to race/ethnicity/gender-defined constructions, class becomes heterogeneous in more urbanized areas.¹⁴

While none of the other variables—Poverty, Unemployment,¹⁵ and Hate Crimes—are statistically significant, it is worth noting that Hate Crimes does not correlate with the *SoHI* rankings. This would support the premise that hate crimes are an essential part of unmasking hate in the United States, but are not yet reliable for comparing one state to another. For instance, observe how New York ranks 1st for Overall Rank and 38th for Hate Crimes. Meanwhile, Mississippi is 38th for Overall Rank and 1st for Hate Crimes (See Table 6). As stated earlier, some state justice systems seem more likely to classify and prosecute hate crimes, which could give the appearance of greater hate in that region.

TABLE 6: REGRESSION RESULTS FOR SOHI RANKINGS WITH INCOME INEQUALITY, POVERTY, UNEMPLOYMENT, URBANIZATION AND HATE CRIMES

	MODELS		
VARIABLE	A	B	C
Income Inequality	-633* (-2.28)		
Poverty			.234 (0.12)
Unemployment		-2.02 (-0.31)	
Urbanization	-2.12*** (-5.41)	-2.35*** (-5.82)	-2.39*** (-5.81)
Hate Crimes	.331 (.050)	.604 (0.09)	19.8 (0.36)
Constant	623*** (4.95)	356*** (7.94)	344*** (8.04)
States (N)	51	51	51

Notes: *, **, *** = .05, .01, .001 levels of significance.

As mentioned, all of the findings from the linear regression should be taken as exploratory and explanatory, but not as predictive. As the statistical universe for tracking hate becomes more and more refined and profuse, we can hopefully move towards an even deeper understanding of the dynamics of hate, weaving together qualitative and quantitative research.

Conclusion

The *State of Hate Index* is the first glimpse of how hate manifests from state to state. It is nowhere near the sharpest picture of the fields of hate in America. It is, however, a sharper view of the dynamics as a whole, drawn from the most accurate data sources existing to date. Much more refinement is needed. Asian American, Muslim American, Arab American and Latinx-based hate is included in the general framework of *SoHI*, but it is not broken down into separate, stand-alone variables. Hatred toward these groups has become more apparent in the media since the September 11th attack on the World Trade Center and the rise to presidency of Donald Trump.¹⁶ Coalitions, such as Stop AAPI Hate, are producing more reliable reporting systems for hate directed at Asian Americans and Pacific Islanders.¹⁷ We need even more accounting of hate-based destruction of property and lives. Additionally, policies and laws matter. The wide range of what lawmakers are willing to do to protect vulnerable groups is readily apparent in the *SoHI*. Raising the costs for harm to others works, and legislators who ignore this endanger the citizens who enter, and live within, their state borders.

TABLE 7: SOHI OVERALL RANK COMPARED TO HATE CRIMES RANK

STATE	OVERALL RANK	HATE CRIMES RANK
New York	1	38
Hawaii	2	16
Illinois	3	12
California	4	41
Connecticut	5	39
New Jersey	6	48
Maryland	7	9
Massachusetts	8	49
Florida	9	8
Delaware	10	33
District of Columbia	11	51
Iowa	11	4
Minnesota	11	40
Nevada	11	13
Rhode Island	15	19
New Mexico	16	20
Pennsylvania	17	5
Missouri	18	25
Texas	19	10
Washington	20	50
Kansas	21	34
North Carolina	22	30
Tennessee	23	35
Louisiana	24	6
Utah	24	21
Colorado	26	36
Ohio	27	42
Wisconsin	28	7
Oregon	29	43
Vermont	29	45
Michigan	31	46
West Virginia	32	22
Virginia	33	28
Georgia	34	14
Arizona	35	44
Oklahoma	36	11
Maine	37	37
Kentucky	38	47
Mississippi	38	1
Alabama	40	2
Indiana	41	31
North Dakota	41	23
Alaska	43	15
Nebraska	43	26
New Hampshire	45	27
South Carolina	46	18
Arkansas	47	3
Wyoming	48	24
South Dakota	49	29
Montana	50	17
Idaho	51	32

NOTES

1. Robert Tynes Ph.D. is a political scientist who researches political violence, child soldiers, online activism, and African politics. He is the director of research and site director for the Bard Prison Initiative.
2. The Bard Center for the Study of Hate supported this project, from conceptualization to print (and secured a grant to underwrite the work from GS Humane Corporation). Thank you to Hannah Henry, who helped with research. Kenneth Stern provided invaluable feedback throughout the project—thank you. Cathy Buerger, Kristin Lane, and Jack McDevitt were very generous, reviewing an early draft of the paper—thank you for your keen eyes. And thank you to Maria Simpson, who also offered a thorough review of the manuscript. Finally, thank you to Mary Smith, Leslie Coons Bostian, and Karen Spencer of the Bard Publications Office.
3. Violence is defined as any action that results in psychological, symbolic, property, or bodily damage.
4. SoHI also includes the District of Columbia.
5. Green, Victor H. (1937-1962). *The Negro Motorist Green Book* (Vol. 1-20). New York, New York: Victor H. Green & Company.
6. Taylor, Candacy (2016). “The Roots of Route 66.” *The Atlantic*, 3 November 2016. Available at: <https://www.theatlantic.com/politics/archive/2016/11/the-roots-of-route-66/506255/>
7. In this quote, Bourdieu, Wacquant, and Farage reference to states pertains to countries. Nevertheless, the same phenomenon is applicable to the federal system of states in America.
8. See Yam (2021) regarding underreporting by the AAPI community; Stop AAPI Hate (2021) started tracking incidences of hate against AAPI in March 2020. Its 2020-2021 National Report offers detailed data on types of discrimination, sites of discrimination, and a list of some of the top states by number of incidents. The Center for the Study of Hate and Extremism (2021) also has compiled valuable statistics on anti-Asian hate crimes. Hopefully these data collection efforts will continue and become more detailed and robust at the state level.
9. All the variables used for the SoHI and for the regression analysis are discussed in greater detail in Appendix A.
10. For a much more sophisticated discussion regarding law, norms, and narrative see: Cover, Robert (1993). “Nomos and Narrative.” In Martha Minow, Michael Ryan, and Austin Sarat (eds.), *Narrative, Violence, and the Law: The Essays of Robert Cover*. Ann Arbor: University of Michigan Press: 95-172.
11. Note that the SoHI model is not intended to be absolute. Other researchers may find different ways of measuring and ranking, and we invite that further discussion and refinement.
12. Also see Kaufman (2001); and, of note, van Dijk (1993).
13. See Appendix A for the variables discussed in more detail.
14. Panning (1983) details how research on relative deprivation and income equality finds variation in the correlation—some uncorrelated and some negative. He suggests that we also include the likelihood that people will compare themselves to one another economically.
15. Green and Strolovitch (1998) found little connection between unemployment and hate-motivated actions.
16. See Kuek Ker (2016); Mosley (2019); Pilkington (2021); Hong and Bromwich (2021).
17. See <https://stopaapihate.org/about/>
18. A correlation matrix was run for the variables of Number of Hate Groups, Violence against Women, Anti-Semitic Violence, and White Supremacy Violence, checking for multicollinearity. No significant collinearity was found.

REFERENCES

- Anti-Defamation League (2020). "ADL H.E.A.T. Map: Hate, Extremism, Antisemitism, Terrorism." Available at: <https://www.adl.org/education-and-resources/resource-knowledge-base/adl-heat-map>
- Bourdieu, Pierre, Loïc J. D. Wacquant, and Samar Farage (1994). "Rethinking the State: Genesis and Structure of the Bureaucratic Field," *Sociological Theory*, Vol. 12, No. 1, pp.
- Bourdieu, Pierre. *On the State: Lectures at the Collège de France 1989-1992*. Edited by Patrick Champagne, Remi Lenoir, Franck Poupeau, and Marie-Christine Rivière, translated by David Fernbach. Cambridge, UK: Polity Press, 2014.
- Craig, Kellina M. (2002). "Examining Hate-motivated Aggression: A Review of the Social Psychological Literature on Hate Crimes as a Distinct Form of Aggression." *Aggression and Violent Behavior* 7: 85-101.
- Center for the Study of Hate and Extremism (2021). "Anti-Asian Prejudice." *Fact Sheet March 2021*. Available at: <https://www.csusb.edu/sites/default/files/FACT%20SHEET-%20Anti-Asian%20Hate%202020%203.2.21.pdf>
- FBI (2016). "Table 11: Offense Type by Participating State, 2016" *Federal Bureau of Investigation 2016 Hate Crime Statistics*.
- FBI (2017). "Table 11: Offense Type by Participating State, 2017" *Federal Bureau of Investigation 2016 Hate Crime Statistics*.
- FBI (2018). "Table 11: Offense Type by Participating State, 2018" *Federal Bureau of Investigation 2016 Hate Crime Statistics*.
- FBI (2020). "What We Investigate: Civil Rights: Hate Crimes." Available at: <https://www.fbi.gov/investigate/civil-rights/hate-crimes>
- Geertz, Clifford (1977). *The Interpretation of Cultures*. New York: Basic Books.
- Gerney, Arkadi and Chelsea Parsons (2014). "Women under the Gun: How Gun Violence Affects Women and 4 Policy Solutions to Better Protect." Center For American Progress.
- Green, D. P., & D. Z. Strolovitch (1998). "Defended neighborhoods, integration, and racially motivated crime." *American Journal of Sociology*, 104, 372-404.
- Gurr, Ted (1970). *Why Men Rebel*. Princeton, NJ: Princeton University Press.
- Hong, Nicole and Jonah E. Bromwich (2021). "Asian-Americans Are Being Attacked. Why Are Hate Crime Charges So Rare?" *New York Times*. 18 March, 2021. Available at: <https://www.nytimes.com/2021/03/18/nyregion/asian-hate-crimes.html>
- Human Rights Campaign (2020). "State Map of Laws and Policies" Human Rights Campaign. Available at: <https://www.hrc.org/state-maps>
- Craig, Kellina M. (2002). "Examining Hate-motivated Aggression: A Review of the Social Psychological Literature on Hate Crimes as a Distinct Form of Aggression." *Aggression and Violent Behavior* 7: 85-101.
- Ilganski, P., and Levin, J. (2004). "Cultures of hate in the urban and rural: Assessing the impact of extremist organizations." In N. Chakraborti and J. Garland (Eds.), *Rural racism*. Cullompton, UK: Willan Publisher: 108-121.
- Kaufman, Stuart J. (2001). "Modern Hatreds: The Symbolic Politics of Ethnic War." Ithaca: Cornell University Press.
- Kuek Ker, Kuang Ken (2016). "Data: Hate Crimes against Muslims Increased after 9/11." *The World*, Public Radio International (PRI). Available at: <https://www.pri.org/stories/2016-09-12/data-hate-crimes-against-muslims-increased-after-911>
- Levin, Brian and Lisa Nakashima (2019). "Report to the Nation: 2019." Factbook on Hate and Extremism in the U.S. and Internationally. Center for the Study of Hate and Extremism, California State University, San Bernardino.
- Levin, J. and J. McDevitt (1993). *Hate Crimes: The Rising Tide of Bigotry and Bloodshed*. New York: Plenum.
- Mosley, Tonya (2019). "The 'Forgotten' History of Anti-Latino Violence." *Here and Now*, WBUR Radio. Available at: <https://www.wbur.org/hereandnow/2019/11/25/history-violence-against-latino>
- National Conference of State Legislatures (2021). "State Partisan Composition" 23 February 2021. Available at: <https://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx>
- National Conference of State Legislatures (2020). "State Partisan Composition." Available at: <https://www.ncsl.org/research/about-state-legislatures/partisan-composition.aspx>
- Panning, William H. (1983). "Inequality, Social Comparison, and Relative Deprivation," *American Political Science Review* 77: 323-329.
- Pilkington, Ed (2021). "FBI under Pressure to Tackle Anti-Asian Hate Crime in Wake of Atlanta Shootings." *The Guardian*. 18 March, 2021. Available at: <https://www.theguardian.com/us-news/2021/mar/18/fbi-pressure-anti-asian-hate-crime-atlanta>
- Sheskin, Ira M. and Arnold Dashefsky (2021). "United States Jewish Population, 2019," In Arnold Dashefsky and Ira M. Sheskin (Eds.), *American Jewish Year Book, 2020*, Cham, Switzerland: Springer.

- Smith, Sharon G., Jieru Chen, Kathleen C. Basile, Leah K. Gilbert, Melissa T. Merrick, Nimesh Patel, Margie Walling, and Anurag Jain (2017). "The National Intimate Partner and Sexual Violence Survey (NISVS): 2010–2012 State Report." National Center for Injury Prevention and Control Centers for Disease Control and Prevention.
- Southern Poverty Law Center (2020a). "Hate Map." Data available for download at: <https://www.splcenter.org/hate-map>
- Southern Poverty Law Center (2020b). "Methodology: How Hate Groups are Identified and Categorized." Available at: <https://www.splcenter.org/news/2020/03/18/methodology-how-hate-groups-are-identified-and-categorized>
- Stern, Kenneth (2004). "The Need for an Interdisciplinary Field of Hate Studies." *Journal of Hate Studies* 3(1): 7–35.
- Stop AAPI Hate (2021). "2020–2021 National Report." StopAAPIHate.org. Available at: <https://stopaapihate.org>
- U.S. Bureau of Labor Statistics (2020a). "Local Area Unemployment Statistics: Unemployment Rates for States." Available at: <https://www.bls.gov/lau/tables.htm>
- U.S. Bureau of Labor Statistics (2020b). "Labor Force Statistics from the Current Population Survey." Available at: <https://www.bls.gov/cps/definitions.htm#ur>
- U.S. Census Bureau (2018). "2018 National and State Population Estimates." Available at: <https://www.census.gov/newsroom/press-kits/2018/pop-estimates-national-state.html>
- U.S. Census Bureau (2020a). "Gap between rich and poor, by state in the U.S. 2019." U.S. Census Bureau statistics as compiled by Statista.
- U.S. Census Bureau (2020b). "Interrelationships of Three-Year Average State Poverty Rates: 2016–2018 (Current Population Survey, March 2017–2019)." Available at: <https://www.census.gov/data/tables/2019/demo/income-poverty/p60-266.html>
- U.S. Census Bureau (2020c). "Urban Percentage of the Population for States, Historical." Data drawn from 2010 as compiled by Iowa Community Indicators Program, Iowa State University. Available at: <https://www.icip.iastate.edu/tables/population/urban-pct-states>
- U.S. Census Bureau (2020d). "How the Census Bureau Measures Poverty." Available at: <https://www.census.gov/topics/income-poverty/poverty/guidance/poverty-measures.html>
- Van Dijk, Teun A. (1993). *Elite Discourse and Racism*. London: Sage Publications.
- Wilson, M. S., and Ruback, R. (2003). "Hate Crimes in Pennsylvania, 1984–99: Case Characteristics and Police Responses." *Justice Quarterly* 20(2): 373–398.
- Yam, Kimmy (2021). "Asian Americans Are Least Likely to Report Hate Incidents, New Research Shows." *NBCNews.com*. 31 March, 2021. Available at: <https://www.nbcnews.com/news/asian-america/asian-americans-are-least-likely-report-hate-incidents-new-research-n1262607>
- Yitzhaki, Shlomo (1979). "Relative Deprivation and the Gini Coefficient," *Quarterly Journal of Economics* 93: 321–324.

APPENDIX A: FURTHER NOTES ON METHODOLOGY

1. Variables for the *SoHI*

Variables for the *SoHI* were chosen based on reliability, accuracy, and timeframe. There is no definitive dataset for hate-based actions. The *SoHI* is an attempt to build towards greater precision. For now, the state level of analysis held the most reliable statistics across categories. The timeframe spans 2010–2020. However, that does not mean that all of the data covers each and every year. Some data is only reliable for 2010–2012, while other data covers 2016–2018. Because of this, the focus is on depicting the general field of hate during this decade, and not drawing year-to-year causal connections. Also, not all groups that are discriminated against could be represented equally. As highlighted in the conclusion, groups such as Asian Americans are represented in the data in general, which is not optimal for understanding a serious, and long-standing, problem of hate in the United States. Nevertheless, Asian Americans are considered a part of the Index in the variable of General Laws and Policies Relating to the Prevention of Hate. The following list each variable and how the data was gathered and processed for use in the Index. District of Columbia is included with the states in recognition of its near-state status.

Number of Hate Groups¹⁸

The Number of Hate Groups is drawn from the Southern Poverty Law Center's (SPLC) database (2020a) on hate groups in the United States as of 2018. SPLC (2020b) defines 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." The raw number of hate groups per state is divided by the population for that state in 2018 (U.S. Census Bureau 2018). The ratio is then used for the state ranking with 1 = lowest percentage and 51 = highest percentage.

Violence Against Women

The Violence against Women variable is constructed from data compiled for the National Intimate Partner and Sexual Violence Survey (NISVS) 2010–2012. (Smith et al 2017). The NISVS calculates what percentage of the population has experienced sexual violence for women and for men and with further breakdowns by race/ethnicity. For the *SoHI*, the "Contact Sexual Violence for Women" percentage was utilized. Smith et al (2017) define contact sexual violence as including "rape, being made to penetrate someone else, sexual coercion, and/or unwanted sexual contact" (p. 19). Sexual violence against women is not a hate crime, but it does represent the dehumanization/othering of women, which is the essential dynamic of hate. The NISVS percentage was converted to a rank for the *SoHI*. States are then ranked by percentage with 1 = lowest percentage and 51 = highest percentage.

Anti-Semitic Violence

The Anti-Semitic Violence variable is calculated from research conducted by the Anti-Defamation League (ADL) (2020). The data spans from 2016–2020. ADL counts number of incidents by state, defining incidents as: "Criminal and non-criminal incidents of harassment, vandalism, and assault or other violence that: 1) include circumstances indicating anti-Jewish animus on the part of the perpetrator; or 2) result in Jewish individuals or organizations being victimized due to their Jewish or perceived Jewish identity." The *SoHI* uses the raw incident count per state divided by the Jewish population for that state (Sheskin and Dashefsky 2021). The ratio helps reveal the impact on the Jewish population. The higher the percentage, the greater the effect. States are then ranked by percentage with 1 = lowest percentage and 51 = highest percentage.

White Supremacy Violence

The White Supremacy Violence variable is calculated from research conducted by the Anti-Defamation League (ADL) (2020). The data spans from 2016–2020. ADL counts number of events and propaganda incidents by state. White supremacist events are defined as: "Public and private events in the United States organized or attended by white supremacists, including rallies and protests, counterprotests, white-power music events, flash mob demonstrations, hate group meetings, and more." White supremacist propaganda is defined as: "Incidents of white supremacist propaganda distribution, including flyers, handbills, posters, stickers, leaflets, and banners." White supremacist graffiti is not included. Information on these incidents comes from media, law enforcement, and constituent reporting as well as direct observations of extremist social media. (See "Information" for "Incidents" on ADL H.E.A.T. Map webpage [ADL 2020]). The *SoHI* uses the raw incident count per state divided by the Black population for that state (U.S. Census Bureau

2018). The Black population statistic was chosen as a proxy for minority-impacted groups in the state. This is not to say that the hate generated by White supremacy violence is not harming other minority groups as well. Statistics on Black populations tended to be the most reliable for minority groups, and therefore more accurate for use in analysis. The higher the percentage, the greater the effect. States are then ranked by percentage with 1 = lowest percentage and 51 = highest percentage.

General Laws and Policies Relating to the Prevention of Hate

General Laws and Policies data is culled from Levin and Nakashima (2019). These researchers list the hate crime statutes that exist in each state, coding each one as either “yes” or “no.” There are 10 categories of statutes: Race/Religion/Ethnicity, Gender, Gender Identity, Age, Sexual Orientation, Disability, Homelessness, Political Affiliation, First Responders/Police, and Interference with Religious Services. The *SoHI* utilizes eight of the 10 categories, leaving out Political Affiliation and First Responders/Police. The categories are converted from dichotomous scores (0 = no; 1 = yes) into weighted scores to account for greater discernment on the part of the state. For instance, Race/Religion/Ethnicity is weighted as 1 whereas Gender Identity is weighted as 3. Laws that are more specific and exacting receive a higher weight. For instance, laws against Interference with Religious Services scored 5, versus Race/Religion/Ethnicity, which is weighted as 1. The weighted scores are added together across categories for each state to produce a raw weighted score. The overall rank is determined as the higher the raw weighted score, the greater the protections against hate. For example, District of Columbia had a raw score of 13 and an overall rank of 1 (the greatest level of protections), whereas Arkansas, Georgia, Indiana, South Carolina and Wyoming all had a raw score of 0 and overall rank of 47 (tied for the lowest level of protections).

Laws and Policies LGBTQ

Laws and Policies LGBTQ data is tallied from the Human Rights Campaign’s (HRC) (2020) maps on state laws and policies as of 2020. HRC tracks laws and policies protecting people who identify as LGBTQ. States are coded according to multiple types of antidiscrimination laws and policies. The *SoHI* incorporates the following eight HRC categories: Anti-Conversion Therapy, Gender Marker Updates on Identification Documents, Transgender Healthcare, Education, School Anti-Bullying, Public Accommodations, Employment, and Housing. For *SoHI*, some of the categories are coded from -1 to 2. The negative coding is for laws or policies that discriminate. For example, in South Dakota, there are state laws and policies that limit the inclusion of LGBTQ topics in schools, so it is coded as -1. Conversely, Arkansas has laws and policies that explicitly prohibit “harassment and/or bullying of students based on sexual orientation and gender identity” (HRC 2020). Hence, Arkansas is coded as “2”. The composite score for the eight categories is totaled for a raw score. The raw score is converted to an overall rank for Laws and Policies LGBTQ with 1 being the best score and 46 being the worst score.

Guns and Domestic Violence Policies

Guns and Domestic Violence Policies are an attempt to measure protections for women against hate, specifically from their domestic partners. Gerney and Parsons (2014) study violent crime in the United States, noting that “the burden of this violence falls overwhelmingly on women” (p. 5). Their analysis includes an accounting of state laws protecting domestic partners against potential gun violence, as of June 2014. These are the eight categories in their analysis that are utilized for *SoHI*: Gun Possession Bar on Individuals Convicted of Misdemeanor Domestic Violence Crimes; Gun Possession Bar on Individuals Subject to Domestic Violence Protection Orders; Gun Possession Bar on Individuals Convicted of Misdemeanor Sex Crimes; Gun Possession Bar on Individuals Convicted of Misdemeanor Stalking Crimes; Bar for Misdemeanor Domestic Violence Crimes, including “Dating Partners”; Required Surrender of Certain Firearms by Persons Convicted of Misdemeanor Domestic Violence Crimes; Required Surrender of Certain Firearms by Persons Subject to Domestic Violence Restraining Orders; and, Required Removal of Certain Firearms by Law Enforcement at Specified Domestic Violence Incidents (pp. 35–36). Gerney and Parsons (2014) code as either “yes” or “no”. Their dichotomous scale is changed to “1” or “0” for *SoHI*. The scale range becomes 0–8 with eight being the most protections. The final ranking is 1–34 (some states have the same score), with 1 equal to most protections and 34 equal to least protections.

2. Variables for the Linear Regression

The linear regression takes the *SoHI* Total as the dependent variable (DV), and income inequality, poverty, unemployment, urbanization, and hate crimes as the five independent variables. A variance inflation factor (VIF) test showed no multicollinearity overall. Running a correlation matrix revealed some collinearity, which is why three Models (A–C) were constructed. Results revealed that Urbanization was significant at the .001 level and Income Inequality at the .05 level.

SoHI Total (DV)

SoHI Total is the dependent variable (DV) used. It has a range from 63–285. It is used instead of the final Overall Rank in order to adjust for heteroskedasticity.

Income Inequality (IV)

Income Inequality is an independent variable (IV) measured by the Gini Index. The index is a coefficient that ranges from 0–1. The U.S. Census Bureau (2020a) states “the Gini Coefficient is calculated by looking at average income rates. A score of zero would reflect perfect income equality and a score of 1 indicates a society where one person would have all the money and all other people have nothing.” The *SoHI* ranks the Gini Index, setting 1 as least inequality and 51 as greatest inequality compared to the other states

Poverty (IV)

Poverty is an independent variable (IV) drawn from the U.S. Census (2020b) data for the three-year interrelationship of poverty rates for 2016–2018. The variable is defined as: “a set of money income thresholds that vary by family size and composition to determine who is in poverty. If a family’s total income is less than the family’s threshold, then that family and every individual in it is considered in poverty. The official poverty thresholds do not vary geographically, but they are updated for inflation using the Consumer Price Index” (U.S. Census Bureau 2020d). The Poverty variable for the linear regression is measured as the straight percentage for each state.

Unemployment (IV)

Unemployment is an independent variable (IV) measured as a rate, drawn from the U.S. Bureau of Labor of Statistics (2020a) for 2016–2019. The unemployment rate is “the number of unemployed people as a percentage of the labor force (the labor force is the sum of the employed and unemployed). The unemployment rate is calculated as: (Unemployed ÷ Labor Force) x 100 (U.S. Bureau of Labor Statistics (2020b). The Unemployment variable for the linear regression is the straight percentage average for all four years for each state.

Urbanization (IV)

Urbanization is an independent variable (IV) measured as the percentage of the urban population for a state in 2010. This is the most up-to-date year for this statistic. Urban percentage is calculated from “all population in urbanized areas and urban clusters (each with their own population size and density thresholds)” divided by the overall population of the state (U.S. Census Bureau 2020c). The Urbanization variable for the linear regression is the straight percentage average for each state.

Hate Crimes (IV)

Hate Crimes is an independent variable (IV) drawn from the FBI database for the years 2016–2018. The FBI defines hate crime as a “criminal offense against a person or property motivated in whole or in part by an offender’s bias against a race, religion, disability, sexual orientation, ethnicity, gender, or gender identity” (FBI 2020). The *SoHI* utilizes seven categories of hate crimes, the more aggressive and violent acts: murder and non-negligent manslaughter; rape; aggravated assault; simple assault; intimidation; arson; and destruction/damage/vandalism. All the incidents for each category are added together for the yearly total, and then all three of the year totals are added together for a grand total of incidents. The grand total is then divided by the state population. The final percentage, converted to a log, is what is used for the linear regression in order to adjust for heteroskedasticity.

3. Other Variables**State and Legislative Partisan Composition**

State and Legislative Partisan Composition is the overall party control of the state as determined by the legislative controlling party plus the governor controlling party. The timeframe spans 2015–2019, looking at the general trend for those five years. Data is drawn from research by the National Conference of State Legislatures (2020).



Bard | CENTER FOR THE
STUDY OF HATE