Hate Crime Does Not Predict Trump Support, but Non-Reporting of Hate Crime Does

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Table of Contents

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Chapter 1: The Rise of Trump

Very few people predicted the Trump phenomenon. Many people were left with the question: how did someone with no political experience make it to the White House? Was it his isolationist foreign relations positions, economic platform targeting the blue collar middle class, anti-minority social rhetoric, or something else? Some people say his supporters do not fit into consistent demographic patterns or ideological positions. To them, his election represents social and political rebellion against the status quo (Sides 2016). Looking at the situation from that angle, the question then becomes what are the underlying social and political factors that fueled this rebellion? This is a larger question than "Why did people vote for Trump?"; this is a question that tries to understand the dissatisfaction that led to the election of a populist candidate. While these questions may seem the same to some, they are distinct. The first assumes people are supporting a candidate for his specific views, positions, and policies, while the second speaks to *why* the American people supported a symbol of anti-establishmentarianism.

Many political scientists have attempted to answer these difficult questions, though they have not reached a consensus. Some simply see it as a demographics win for Trump. He was able to mobilize the white, less educated, rural, and evangelical factions of our country more than anyone expected, while Clinton failed to mobilize minorities, urban populations, and secular voters to the same extent (Brockway 2016; Rodden 2017). Most, however, are entrenched in the debate of whether it was economic or social—read racial—anxiety (Birnir 2016; Casselman 2017; Cerrato 2016; Collingwood 2016; Major 2016; Tesler 2016; Yanagizawa-Drott 2016). The way these authors define and describe social and economic anxiety varies, but generally, there seems to be common threads among each camp. Researchers describe and analyze economic anxiety using myriad proxies from living in a post-industrial town, or one that is more vulnerable to import competition with China or Mexico, to the more traditional unemployment, job losses to globalization, or surveys measuring economic optimism for the future (Casselman 2017; Cerrato 2016; Rothwell 2016). Researchers describe social anxiety in much the same way as economic anxiety, in that it is described in every way imaginable—from the influx of immigration in a certain area, or feelings toward one's own racial group, to the loss of social mobility, or the larger anxiety surrounding perceived loss of white power (Birnir 2016; Klinkner 2016; Major 2016; Rothwell 2016; Tesler 2015, 2016; Thompson 2016).

These opposing sides of debate share a common goal: they attempt to understand the demographics that led to Trump support in the context of a larger explanation. Though these larger explanations—economic and social anxiety—are often presented as conflicting views using different proxies to describe them, most do share a common undertone. This undertone is the feeling that the American Dream is failing, and [white] people are worse off now, socially and economically, than their parents or grandparents were at their age (Cramer 2016; Rothwell 2016; Sides 2016; Thompson 2016; "Kaiser […]" 2016). Experts are arguing opposite sides, using vastly different data, and still, when they step back to draw larger conclusions, they are saying the same thing—white America is anxious and unhappy. The point is not which explanation or narrative (economic or social) is more correct because, more likely than not, they are both correct (Casselman 2017; Thompson 2016). The point is that economic and social anxiety are not mutually exclusive, and moreover, they tend to be mutually reinforcing. Further, they are two parts of a larger, underlying issue: racism (Thompson 2016).

Racism is a very broad term, and though political scientists have argued it is too simplistic, I believe that the specific proxies listed above for measuring economic and social anxiety are too narrow to encompass the larger trend of white dissatisfaction and disillusionment with the government. I argue that this dissatisfaction is not a result of recent social or economic anxiety brought about by the 2016 election but is instead the most recent chapter in a backlash against the changing demographic of the nation and Democratic party (Abrajano 2015). While racism is not the sole reason Trump was elected, it does explain why there is no clear winner in the economic versus social debate: economic and social anxiety are masking racism. Racism flourishes during periods of weak economic growth or recession and an increasing minority population (Thompson 2016). Racism also puts white dissatisfaction into context because when the majority group feels socially or economically threatened, as during periods of weak economic growth or recession and increasing minority population, they turn to nationalism and nativism to consolidate what they perceive as rightfully theirs (Swain 2004; Thompson 2016). Trump played on white America's nativist anxieties with his "Make [white] America Great Again" slogan and it won him the presidency.

Though this paper will be rooted in the expansive voting literatures, there is far less material surrounding the voting tendencies of democracies when confronted with populist candidates, and almost nothing that attempts to link voting, the election of populist candidates, and racism using quantitative analyses. The literature on Trump, while large for the timespan, is still very young. Political scientists and researchers of every field will be studying this election for years, perhaps centuries, to come. My contribution to this literature will be to answer the question: *Can non-reporting of hate crimes predict Trump support?* More specifically, is there a correlation between instances of non-reporting of hate crime by county in 2015 and vote share for Trump in the 2016 general presidential election? The term "non-reporting" in this paper means counties that do not report hate crimes to the FBI.

Non-reporting of hate crimes aggregated at the county level is my measure of racism. Though hate crime is an obvious measure of racism, non-reporting of hate crimes is not so obvious. Lawyers at the Department of Justice say there are two reasons counties do not report hate crimes: (1) They do not have the financial resources; (2) They do not care (Wong).[1] I believe the latter and will use 2014 IRS tax data per capita as a measure of fiscal county capacity to control for the former.

My main argument is that local elected officials in counties that do not report hate crimes do not report because they do not care. There are many reasons why these officials may not care about hate crime reporting. Their state might not require them to report so there is less incentive, or if it is required, then they are reflecting local public opinion, which may not deem it important. [2] Though elected officials do not comprise the majority of law enforcement, the positions that they hold are influential. Governors and local sheriffs respond to public opinion, and the public elects those they feel share similar values. Similarly, even though non-elected law enforcement officials do not have to contend with reelections, they are still susceptible to public opinion. A county that does not report hate crimes, if it is not constrained economically, is at the very least indifferent to hate motivated crimes, and at most complicit in their proliferation.

I hypothesize that non-reporting counties will be able to predict areas of high Trump support. I predict there will be a positive correlation between Trump support and the non-reporting of hate crimes by county. In other words, counties that do not report hate crimes will

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[1] This information comes from my advisor Professor Tom Wong's contacts at the Department of Justice.

[2] Only five states have no state-level hate crime legislation in place. They are Arkansas, Georgia, Indiana, South Carolina, and Wyoming ("#50StatesAgainstHate: An Initiative for Stronger Hate Crime Laws").

have significantly higher levels of Trump support than counties that do report hate crimes. Non-reporting of hate crime is the variable of interest because it is the best measure of systematic hate crime data available. The reported hate crime data published by the FBI is flawed. It is flawed because while the Attorney General is mandated by congress to track and publish hate crime data annually, states are encouraged, but not *required,* to submit hate crime data (King 2007). This creates a response bias in the data where counties that track and submit data in good faith seem to have a hate crime problem and counties that do not, appear to have no problem.

My dependent variable is Trump support measured by vote share in the 2016 general election by county. These results were gathered before states posted official election results, and although they were the best available at the time, it is possible the data presented here is different than the official published data by each state's secretary of state ("Presidential Election Results: Donald J. Trump Wins"; Leip). My first regression model (**Model 1**) runs Trump support against *% White, not Latino*, *Median Household Income*, and *% BA or higher* (Table 2). These variables are all taken from the 2015 ACS 5-year estimates (Data Access and Dissemination Systems (DADS)). **Model 1** acts as the foundation for all models because it contains the independent variables that are most commonly associated with Trump support.

Model 1 is a good fit because the outcomes of *areas* supporting Trump, not people, are as expected—statistically significant positive correlations between Trump support and both *% White, not Latino* and *Median Household Income,* and a statistically significant negative correlation between Trump support and *% BA or higher.* Trump catered his campaign to white, less educated populations, and both the literature and the results of **Model 1** confirm that assumption. The positive correlation seen with *Median Household Income* may seem surprising, but what must be understood is that while people in these areas may be economically *anxious*, they are not undergoing economic *hardship* (Casselman 2017; Silver 2016; "Kaiser […]" 2016).

Model 2 contains the independent variable of interest—*Hate Not Reported*. *Hate Not Reported* is the non-reporting of hate crimes that are derived from the FBI's Uniform Crime Reporting (UCR) for 2015 by county ("Table 14 […]"). **Model 2** also controls for county capacity by *$ Per Capita,* which is the total tax receipts from the 2014 IRS County Tax Data divided by the population from the 2015 ACS 5-year estimates (Wong; Data Access and Dissemination Systems (DADS)). For consistency, it also maintains the controls present in **Model 1**—*% White, not Latino*, *Median Household Income*, and *% BA or higher*. I found that counties that did not report hate crimes had significantly higher levels of Trump support than those counties that did report hate crimes. These conclusions hold at the 99.9% confidence level even when controlling for county capacity, percent white, median household income, and education (Table 2).

Model 3 and **Model 4** attempt to control for the ambiguity that results from a reporting of zero hate crimes by counties. Zeros are ambiguous because they can indicate that a county did not have any hate crimes during that year, or that they did but for whatever reason—not investigating them, do not think they occur, trying to hide racial or minority tensions in their jurisdictions—they report having zero hate crimes. Specific non-reporting theories are discussed in chapter two.

Model 3 measures *Hate Not Reported or Zero*, which groups counties that did not report hate crimes to the FBI in 2015 with counties that reported zero hate crimes to the FBI in 2015 (Table 14 […]"). **Model 3** uses the same control variables that are present in **Model 2**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*. I found that counties that did not report hate crimes or reported zero hate crimes had significantly higher levels of Trump support than those counties that did report hate crimes. These conclusions hold at the 99.9% confidence level even when controlling for county capacity, percent white, median household income, and education (Table 2).

Model 4 measures *Magnitude of Hate (H>0),* which uses reported hate crimes by county in 2015, though it excludes the counties that reported zero hate crimes ("Table 13[…]"; "Table 14[…]"). **Model 4** uses the same control variables that are present in both **Models 2** & **3**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*. I found that there is a statistically significant negative relationship at the 99% confidence level between reported, non-zero hate crimes and Trump support (Table 2). These conclusions hold even when controlling for county capacity, percent white, median household income, and education (Table 2). This is significant because without zeros in the data, the correlation between reported hate crimes in 2015 and Trump support become more positive and less significant than the *Hate Reported* data (appendix).

To summarize, **Model 1** provides credibility for all models because it aligns with trends in variables most commonly associated with counties that have high levels of Trump support. **Models 3** and **4** explore and check against the ambiguity of zeros in the FBI's data, while **Model 2** tests the main hypothesis: can non-reporting of hate crimes predict Trump support by county? The takeaway of this paper is that while hate crimes cannot predict Trump support by county, the non-reporting of hate crimes can.

Next, I will present an overview of the relevant literature and show how my research both coincides and deviates from it. I will then cover my research design and multivariate empirical analysis and end with a discussion of the implications for hate crime laws, policy suggestions, and lastly, implications of a Trump presidency.

Chapter 2: We Did Not See It Coming

2.1 Overview

Trump's presidential win came as a shock to most Democrats and Republicans alike. They saw his rhetoric, tweets, and absence of a conventional political platform, and did not take him seriously. Coastal and urban elites—largely Democrats—tend to be isolated from the surrounding rural, or suburban areas, which are largely Republican strongholds (Bartels 2016; Cramer 2016; Rodden 2017, 2017; Rothwell 2016). Couple that with one-sided social media and biased news sources and it is not hard to see why people did not foresee a Trump presidency.

During and after Trump's win, commentators, political scientists, and many others attempted to explain why very few predicted Trump. Many argued that Trump was a new kind of candidate for a variety of reasons ranging from his populist rejection of the current political elites, to his economic isolationism, to his anti-minority rhetoric (Farrell 2016; Rothwell 2016; Sides 2016). While arguments that claim Trump is a unique phenomenon are comforting because they excuse the wrong predictions, they are false. A candidate like Trump is rare, especially after 1980, though he is not unique (Klinkner 2016). I will argue that the changing attitudes and values in voting over the last forty years paved the way for a candidate like Trump.

2.2 Who Votes?

There is a vast amount of literature concerning voting—who votes, why they vote, whether they vote Democrat, Republican, etc. On the forefront of voting literature in the late twentieth century was Wolfinger and Rosenstone with *Who Votes?* (1980). *Who Votes?* was one of the first sources that delved into analytical research for elections and concluded who votes in a presidential election. They concluded that in the 1972 presidential election, education was the most important factor when determining whether someone would vote, that women voted less than men, and that the old voted less than the young (Wolfinger 1980). They also concluded that although voters had different demographic characteristics than non-voters, the voting population was representative of the population as a whole, so it does not matter who votes (Wolfinger 1980).

More recently, Nagler and Leighley responded to *Who Votes?* with *Who Votes Now? Demographics, Issues, Inequality, and Turnout in the United States* (2013). In a study that analyzed voter turnout in every U.S. election from 1972 to 2008, they concluded that voters are not representative of the entire population, so who votes does matter (Nagler 2013). Further, they concluded that the income bias between voters and non-voters has remained stable in times of increasing economic inequality, that the wealthy vote more than the poor, the more educated vote more than the less educated, the old vote more than the young, and women vote more than men (Nagler 2013).

Though this information is an important base for studying any facet of voting, the question this paper is trying to answer is not "Who votes?" but, "Who voted for Trump?" and "Why would the U.S. vote for a candidate like Trump?" These questions are distinct. The answers to "Who voted for Trump? will be surface-level demographic information, while answers to "Why would the U.S. vote for a candidate like Trump?" will be more complex. However, there are a few missing links between these two questions that need to be clarified. While a consensus around who voted for Trump will arise, and it will include a list of demographic factors, it is unlikely that a consensus around the second question will arise anytime soon. Finally, "Why did people vote for Trump?" stands somewhere in the middle of "Who voted for Trump?" and "Why would the U.S. vote for a candidate like Trump?" Since it overlaps with both questions, it will be discussed in connection with “Who voted for Trump?” and “Why would the U.S. vote for a candidate like Trump?” I first attempt to answer the question: Who voted for Trump?

2.3 Who Voted for Trump?

From social media and news sources, people believed they had a handle on who voted for Trump. They believed that it was poor, uneducated whites living in the middle of the country. Is this true? Yes and no. Yes, it appears that as far as demographics go, people who are less educated, white, evangelical, living in rural areas, and in fear of economic downfall tended to vote for Trump (Brockway 2016; Casselman 2017; Collingwood 2016; Cramer 2016; "Kaiser Family Foundation/CNN Working-Class Whites Poll." 2016; Rodden 2017; Rothwell 2016; Sides 2016). However, the answer is also “no” because there are mixed reports on whether Trump supporters suffer economic hardship, economic anxiety, or any financial burden at all (Casselman 2017; Cerrato 2016; Collingwood 2016; "Kaiser Family Foundation/CNN Working-Class Whites Poll." 2016; Silver 2016; Thompson 2016; Yanagizawa-Drott 2016).

It is my contention that Trump supporters are not suffering from economic hardship, on average, but are suffering from economic anxiety (Casselman 2017; Cerrato 2016; Collingwood 2016; "Kaiser Family Foundation/CNN Working-Class Whites Poll." 2016; Silver 2016; Thompson 2016; Yanagizawa-Drott 2016). Economic *hardship* is one’s dire economic position right now, while economic *anxiety* is concern over one’s future economic position (Casselman 2017). Trump did not win on economic hardship, quite the opposite, but he did win on economic anxiety (Silver 2016; Casselman 2017; Cerrato 2016; Collingwood 2016; Thompson 2016).

Political scientists could not get a straight answer using traditional measures of economic hardship, such as unemployment or poverty, so they turned to more creative measures that reflected economic *anxiety*, such as counties where the jobs are vulnerable to automation or outsourcing, instead of economic *hardship* (Silver 2016; Casselman 2017; Cerrato 2016; Collingwood 2016; Thompson 2016). Why economic anxiety led white Americans to flee to Trump is puzzling because white Americans of all income levels have benefitted more economically under Democratic presidents than Republican presidents (Bartels 2016).

Other political scientists argued it was not one's economic situation at all, but rather social or racial anxiety brought to the surface by Trump's anti-minority, anti-immigration rhetoric that compelled voters to support him (Major 2016; Rothwell 2016; Sides 2016; Tesler 2015, 2016; Thompson 2016). For the purposes of this paper, racial anxiety is the changing demographics of the nation, including the influx of non-white immigrants, and the reactions of white America to these changes. These two theories—economic or social [racial] anxiety—became the premiere debate in political science and it is widely accepted that the answer to "Why Trump" lies somewhere within.

2.4 Why Did People or Counties Vote for Trump?

The economic versus racial debate attempts to understand voter demographics and frame them as part of a larger explanation. This larger explanation is cultural apathy and disillusionment with the government. The economic and racial anxiety debate attempts to answer, "Why did people or counties vote for Trump?" through demographic data and link it to this cultural dissatisfaction. In these articles, racial and economic anxieties were measured in unusual ways, but they both tied back to the idea that the American Dream is failing and [white] people perceive themselves as worse off now than their parents or grandparents were at their age (Cramer 2016; Rothwell 2016; Sides 2016; Thompson 2016; Kaiser 2016).

Indeed, the racial versus economic debate has not been adequately answered because the answer is: they are both correct (Casselman 2016; Thompson 2016). Racial and economic anxiety go hand-in-hand. Racism flourishes during periods of weak economic growth, recession, and/or with increasing minority population (Thompson 2016). Racism also puts white dissatisfaction into context because when the majority group feels socially or economically threatened, as in these specific periods, they turn to nationalism and nativism to consolidate what they perceive as theirs to lose (Swain 2004; Thompson 2016).

The economic-racial debate, and the underlying message of white anxiety, can then be viewed as masking racist anxiety. Political scientists and commentators alike have sensed this cultural, racial apathy (racist anxiety) and have tried to understand it. While some political scientists have argued that this apathy was caused by Trump's candidacy, still others believed that Trump was only the symptom of an underlying, pre-existing American racism (Klinkner 2016). I will argue that while Trump's candidacy may have increased voter apathy and racist anxiety, he did not create it. I will argue that the cultural divide over race, racial polarization in politics, the emergence of a new white nationalism, and the creation of the far-right party in the U.S. has its roots even before the civil rights movement, and that these trends primed the electorate for a Trump presidency.

2.5 Trump Did Not Create Cultural Apathy, But He Benefited from It

From 1932 through 1964, the Democratic party held a majority coalition comprised of Northern liberals and Southern conservatives; the dividing line of politics was economics

(Drutman 2016). The passage of the civil rights laws divided the Democratic party between Northern liberals and Southern conservatives, and created a backlash among the Northern, white working class, and the Southern, white conservatives in the Democratic party (Drutman 2016; Sides 2016; Tesler 2013). This shifted the divisive issue from economics to race, and the Republicans capitalized when the Northern, white working class, and the Southern, white conservatives fled the Democratic party.

When the dividing line of politics became race after the civil rights era, racial rhetoric was excised from political discourse. This stifled overt racism while fostering racial resentment and anxiety (Klinkner 2016; Tesler 2013). From the 1980s onward, there was a slow, forty-year realignment where the demographics of the Democratic and Republican parties switched, and economics took the forefront once again (Drutman 2016). Republicans gained the less educated, rural white conservative voters, while the Democrats gained the more educated, urban white liberal voters (Drutman 2016; Tesler 2013).

During the early 2000s, these less educated, rural, conservative white Republicans were losing their livelihoods and becoming more concerned with immigration and globalization. They did not care as much about limiting the government's reach or free trade as they did about securing their disappearing jobs. The only way the Republican party retained these voters was by convincing them that a large government meant that they, and the rest of the white middle class, would be stuck paying for social relief programs for poor, people of color (Drutman 2016). This strategy further racialized party lines, racialized social programs aimed to help all underprivileged, and led to increased racial resentment among middle class Republicans.

After the election of Obama in 2008 and increased immigration, there was a racist backlash against the perceived gains of minority groups (Sides 2016). Whites with strong white identity and racial attitudes became more socially conservative and Republican because of what Michael Tesler (2013) coins “the spillover of radicalization”—Barack Obama’s historical and cultural significance as the first African American president, which forced Americans to constantly confront their racial attitudes (Tesler 2013). Since, racial attitudes have been able to accurately predict non-race related issues, and these issues have begun to predict partisanship (Drutman 2016; Klinkner 2016; Tesler 2013; Sides 2016).

2.6 The New Radical Right

After white working class Democrats fled to the Republican party in 1980, a subset (not necessarily those that recently defected from the Democratic party) then moved further right—forming the recent far populist right (Sides 2016). This new radical right in America arose in response to the polarization of the parties based on race, and the perceived successes of minority populations linked to the Democratic party (Bustikova 2014). The new radical right does not resemble the radical right of the past, though they share similarities. The old radical right included groups such as the Ku Klux Klan, reached out to only specific audiences, and condoned violence (Swain 2004).

The new radical right in America, referred to as the new white nationalism, has toned down its rhetoric, does not condone violence, and is focused on reaching mainstream audiences (Swain 2004). New white nationalists feel that there is a racial double standard in this country, that immigration is threatening the U.S., and that both threaten what is rightfully theirs (Swain 2004). While the new white nationalism may be separate from Trump’s brand of nativism, it is hard to deny that they share a similar ideology. Trump is part of the new populist right in America that resembles other populist groups in Europe, though it is distinct (Birnir 2016; Sides

2016). While Trump does not hold a populist radical right ideology himself, he caters to populist radical right voters with his antiestablishment rhetoric and nativist sentiments (Sides[Mudde] 2016). The largest difference between Trump's populism and recent European populism is deceivingly simple: America is not Europe. To use American and European populism interchangeably would be to ignore America's long history of deep-seeded racial conflict and resentment. So, while Trump may not be a card-carrying member of the new white nationalism, his rhetoric caters to them. Likewise, while the new American populist right may not be exclusively a white nationalist group, they do share similar nativist ideologies.

2.7 A Vote for the Radical Right?

Though America's long history of racist anxiety may have caused the rise of a new far-right group in the U.S., that does not necessarily mean people who voted for Trump did so because they are racist or in the far right. I have argued theoretically about the racial versus economic debate masking racism, but is there evidence of this? In short, yes, there is. First, white Republican racial resentment has increased compared to white Democratic resentment, and racial resentment among white Southern Evangelical Republicans is greater than both white Northern Evangelical Republicans and white Southern Republicans (Hetherington 2016).

Republicans are thirty percentage points more likely to vote for Trump if they believe that Muslims pose an immediate threat to the U.S. than Republicans who do not view Muslims as an immediate threat (Sides 2016). Republicans who are most opposed to immigration are fifty percentage points more likely to vote for Trump than Republicans less opposed to immigration (Tesler 2015). White Republicans were measured to be more ethnocentric than white Democrats, and white Republicans with the highest levels of ethnocentrism were more likely to support Trump than any other candidate (Kalkan 2016).

Also, Trump did best among Americans who expressed more resentment toward immigrants and African Americans (Tesler 2015). Luttig (2016) conducted an experiment that went a step further than simply proving a correlation between Trump support and animosity towards minority groups. He showed that white Trump supporters are less likely to give an economic assistance policy when cued with pictures of black Americans compared with white Americans (Luttig 2016). This demonstrates that racial animosity motivates Trump voters to make political and/or legislative decisions (Luttig 2016).

I want to highlight the importance of the Luttig (2016) study. All of the other evidence in this subsection is survey data in one form or another. These data are good for gauging an individual's likelihood of voting for Trump when they are primed with a question that attempts to reveal racist feelings, but it is only a correlation. Luttig shows causation and gives direct evidence that links racial animosity—an important value of the radical right—to political decision-making.

Chapter 3: Theory and Hypothesis

3.1 The Theory and its Limitations

This theory is limited by the scarce amount of research conducted on the non-reporting of hate crimes, measures of racism in police departments, and racial bias by local elected officials. There is a body of literature published in the late 1990s and early 2000s that measured a handful of local police agencies' successful adherence to the federal hate crime guidelines, and a related body of literature that investigated what kinds of demographic factors led to higher amounts of hate crime non-reporting (King 2007; Nolan 1999; Walker 1995). These bodies of research were rooted in theoretical explanations of types of law enforcement agencies, the ambiguity of local and federal hate crime definitions, and how different internal or external organizations could lead to faulty reporting, or corruption (Grattet 2005; King 2007; Nolan 1999; Walker 1995).

These studies only analyzed a few counties in the U.S., largely did not speak about national trends, and when they did, only went as far as to say less hate crime reporting occurred in areas with larger black populations (King 2007). King's study (2007) attempts to make an over-arching claim about racism and non-reporting of hate crimes, though it focuses primarily on the type of police agency and geographic region of the country (King 2007).

With the emergence of Trump and his anti-minority rhetoric, the increased amounts of hate crime have garnered media attention, which has led to increased scrutiny of hate crime reporting, though these are largely in news sources and do little beyond lament the poor rate of reporting (The Associated Press 2016; Ronald L. Davis and Patrice O'Neill 2016; Middlebrook 2017). Granted, it is difficult to measure non-adherence of hate crime reporting in a systematic way to begin with, and when one tries to measure or argue that non-reporting of hate crimes is due to any kind of police bias, it becomes exceedingly more difficult.

There is one recent case in New York, however, that demonstrates there is validity in the concern over hate crime reporting and law enforcement bias. In 2013, the Suffolk County Police Department was investigated by the Department of Justice, and their investigation “focused on discriminatory policing allegations, including claims that SCPD discouraged Latino victims from filing complaints and cooperating with the police, and failed to investigate crimes and hate crime incidents involving Latinos” ("United States Agrees to Comprehensive Settlement with Suffolk County Police Department to Resolve Investigation of Discriminatory Policing Against Latinos" 2013). New York is a state with local hate crime legislation, and though they are not comprehensive, they are still present ("#50StatesAgainstHate: An Initiative for Stronger Hate Crime Laws"). If this is an example of one county with some regulations, there are bound to be more like it, and that is not even considering states without any local or state hate crime laws.

3.2 The Theory: Bad Reputation, Non-Elected Officers, and Elected Officials

Non-reporting of hate crimes by county will correlate with high areas of Trump support because of latent racism. No causational link can be made here, though if the hypothesis above is correct, there is a correlation between counties with high Trump support and counties who do not report hate crimes.

Department of Justice lawyers say that counties do not report hate crimes because they either do not have the financial resources to track them, or they do not care to track and/or submit them (Wong). In my analysis, I will control for county capacity per capita to get a better idea of whether counties have the monetary resources to report hate crimes. I predict that counties do not report hate crimes because they do not care. There may be innumerable reasons counties do not care, but I will propose three possibilities: The first is that counties do not want to admit they have a hate crime problem, so they withhold the information from the FBI; the second is that non-elected officers believe their time should be spent on more important things, and so they either do not collect or report hate crime data; the third is that elected officials (sheriffs or governors) are responding to constituent's feelings that hate crime collecting, reporting, or both, are unnecessary.

There are numerous other possibilities, but aside from lack of resources, these seem to be the most straightforward. Since I cannot provide empirical evidence for any of these mechanisms at this time, all three are likely. All three of these theories tie in with racial resentment and nativism. Minorities, and violence against minorities may not be seen as a priority because their lives are presumed to be worth less than white lives. This does not mean that all police officers or elected officials are racist or intentionally ignore hate crimes. This does not even mean that those that fail to submit hate crime data are racist. This means that latent, subconscious racism is a part of our society and needs to be evaluated.

Bad Reputation

Counties do not report they have a hate crime problem to the FBI because they do not want to draw negative attention to their districts, and since hate crime reporting is not mandatory for every state, they can do it. This is the least controversial of the three theories I propose because it does not necessarily imply an intentional biased or negligent act. These agencies are protecting themselves from scrutiny, and while the act of intentional non-transparency is lamentable, it can be understood.

Non-Elected Officers

Non-elected officers and elected officials are both a part of this discussion because there are many ways county law enforcement agencies are organized and enforced. Officers, including police chiefs, are municipal employees that are hired, not elected. Police chiefs, or other law enforcement executives can be independent, or they can answer to a mayor; their police agencies may be autonomous, or dominated by a political machine (Grattet 2005). Considering external or internal influences is important for these theories because bias and corruption in police agencies is not impossible.

Theoretically, non-elected officers come into contact with the surrounding community more than elected officials. These officers are first and second responders who deal with crime and the community directly, and while they do not need the public's opinion to keep their job, they are still influenced by it. They prioritize certain crimes over others, and while hate crime data may be important to researchers, police chiefs or officers may not think it is an important use of their time or resources (Nolan 1999). If these feelings are reinforced by the surrounding community, then it makes it easier for non-reporting to occur.

Elected Officials

The elected officials' theory is very similar to the non-elected officers' theory. Elected officials are not the people dealing directly with crime, but they do oversee the efficient running of law enforcement agencies. "Efficient" here is open to interpretation. An elected official may have a certain problem in their district, say it is drug abuse. That official wants to be reelected, and their constituents are putting pressure on this elected official to solve the county's drug problem. Will this official still invest resources in hate crime investigation and reporting? The literature says that they will not if public opinion does not think it is important, they personally feel it is not important, or they do not believe hate crimes occur in their districts (Nolan 1999; Haider-Markel 2002; Walker 1995).

The consequences of non-reporting are the same for any mechanism. It makes it more difficult for researchers to discover trends in data if the data is not accurate, and it obscures potential trends of institutionalized racism among police agencies. Some may ask why is prioritizing resources bad? Prioritizing is not inherently good or bad. Prioritizing is bad when those decisions result in further victimization of minority groups. Prioritizing other things before hate crime reporting is akin to saying hate crimes are not important. Saying hate crimes are not important is a clear message to minorities that their lives do not matter (The Associated Press 2016). Still, some may ask how is this racism? It is racism because when one deems that minority lives are *not* important, that inherently means white lives *are* important. It means they are worth more, and that is racism.

Chapter 4: Research Design

4.1 Overview

Background on Hate Crime Data

One of the most challenging aspects of this project was finding reliable hate crime data. There are many private, independent organizations that track and analyze hate crimes ("Southern Poverty Law Center"; "Hate Monitor Center"; "Muslim Advocates”). Most of these organizations provide qualitative data about a single victimized group. This qualitative data can come in the form of incident maps or articles. They tend to use different definitions of what constitutes a hate crime and, largely, do not divulge whether these crimes have been confirmed as hate crimes by the police. That is not to say that these organizations are not necessary or important for the safety and protection of our most marginalized groups; it is simply saying that these data are not the best for statistical research.

In 1990, the Hate Crime Statistics Act was passed, which required the Attorney General to include hate crimes in the annual Uniform Crime Reports produced by the FBI (Kennelly 1989). This act was amended in 1994, and then again in 2009 with The Matthew Shepard and James Byrd, Jr., Hate Crimes Prevention Act of 2009, which allowed the Justice Department to aid with state and local investigations of hate crimes, providing additional resources to carry out hate crime investigations, and expanded what types of hate crimes were tracked (King 2007; "The Matthew Shepard And James Byrd, Jr., Hate Crimes Prevention Act Of 2009"). In theory, this is a very important and useful mandate. In practice, it leaves much to be desired.

There are four main issues preventing this mandate from success. First, while federal hate crime laws are in place, states vary in the comprehensiveness of their hate crime legislation ("#50StatesAgainstHate: An Initiative for Stronger Hate Crime Laws"). The lack of uniform policy on hate crimes between states and the federal government creates confusion at the local levels. Five states—Arkansas, Georgia, Indiana, South Carolina, and Wyoming—do not even have hate crime legislation at the state or local levels ("#50StatesAgainstHate: An Initiative for Stronger Hate Crime Laws").

The second reason is underreporting, or even misreporting of hate crimes. Officers dealing directly with the incident must determine whether a biased crime occurred. Then, if bias is suspected, a more qualified officer confirms or rejects the initial officer’s assessment of bias (Law Enforcement Support Section (LESS), and Crime Statistics Management Unit (CSMU)). Hate crimes are severely underreported. The process above gives a clue as to why. Misreporting hate crimes, or leaving out certain details in reports that lead to the rejection of bias are both ways hate crimes continue to be underreported. Hate crimes are not an entirely new category of crime, but rather a traditional crime motivated by the offender’s bias. It was not made into its own category to avoid placing new reporting burdens on law enforcement agencies (Law Enforcement Support Section (LESS), and Crime Statistics Management Unit (CSMU)). While the Attorney General is mandated to track hate crime statistics, that mandate does not *require* states to submit their data to the FBI (King 2007). This is different than the first point because state that do or do not have comprehensive hate crime legislation equally do not have to report their data to the FBI. Simply put, the third obstacle is non-reporting by states.

The fourth barrier to complete and accurate hate crime data is the non-reporting of hate crimes by victims. Certain situations or environments, such as fear and intimidation, prevent or deter victims from seeking legal help, which also contributes to the underreporting of hate crimes. In 2003, the National Crime Victimization Survey (NCVS) by the Bureau of Justice Statistics (BJS) attempted to take a different approach to hate crime reporting. It uses the same definition of hate crime that was passed in the Hate Crime Statistics Act, though it asks victims if they believe the crime committed against them was motivated by bias instead of relying on police reporting (Kennelly 1989; Hate Crime Victimization, 2004-2012 - Statistical Tables).

Many view this new reporting method as more accurately reflecting the actual number of hate crimes committed in the U.S each year (Middlebrook 2017). For instance, there were 293,800 hate crimes reported by the NCVS in 2012, but only 5,796 reported by the FBI's UCR (Hate Crime Victimization, 2004-2012 - Statistical Tables; FBI). The survey estimates that in 2012, about 60% of the hate crimes reported in the survey were not reported to the police. Still, that means that 40% of those almost 300,000 hate crimes—about 117,520—were reported to police. Out of approximately 117,520 hate crimes that were reported to the police, only 5,796 hate crimes were published by the FBI. That is just under five percent. Five percent of hate crimes that were reported to police in 2012 made it into the final published report. While it would be very difficult to change the amount of hate crimes not reported to police, it would be much easier to take measures to increase that 5% statistic. I will discuss these proposed measures later in this paper, but suffice to say that 5% is unacceptable.

The hate crime data I used for this paper was from the FBI's UCR data. The NCVS, arguably a more accurate estimate of hate crimes in the U.S., contains voluntary response bias, and does not cover all states. Many of the other private organizations tracking hate crimes do not have reliable, systematic data. Initially, I attempted to look at the relationship between hate crimes reported in 2015 and Trump support ("Table 13 […]"). I was unable to complete this analysis with any confidence because of missing data. Counties either submitted data to the FBI for all quarters, some quarters, or did not submit anything at all. The data tables from the FBI are recorded by city, county, and agency ("Table 13[…]"; "Table 14 […]"). In the dataset that contains data for zero hate crimes committed ("Table 14 […]"), there were 1,948 cities, counties, and agencies that did not report data for one to three quarters. In this table, there were a total of 3,007 quarters of non-reported data. The counties, cities, and agencies that did not participate—no data submitted—are not present on any of the tables published by the FBI. After all of the cities were placed into counties, and the missing counties were identified, there were a total of 3,384 quarters that had no reported data. In 2015, 2,318 counties either reported zero hate crimes or did not report hate crimes, and 768 counties did not report anything. How I transformed the FBI's data into my dataset is in the "Independent Variables" section.

Areas not Included in this Dataset

The results concluded in this paper are taken from an original dataset that includes every county in the United States, except Kalawao, Hawaii, and the state of Alaska. Kalawao, Hawaii is not included because it is a partial county that has census information, but votes with Maui County ("Office of the County Clerk | Maui County, HI."; "§326-34 County of Kalawao; Governance."). Alaska is not included in this analysis because their voting areas, known as State House Districts, and census areas, are not the same, and are not easily combined ("Overview of Alaska (State)").

4.2 Dependent Variable: Trump Support

Trump support is the dependent variable. It is measured by Trump's vote share by county in the 2016 general presidential election (Presidential Election Results: Donald J. Trump Wins 2016; Leip). This data was gathered when the election results were unofficial, so there may be slight differences between this data and the official data published by each state's secretary of state.

4.3 Independent Variables

The independent variables all stem from the FBI's 2015 hate crime data, specifically Tables 13 and 14, which are hate crimes reported and zero hate crimes reported, respectively ("Table 13[…]"; "Table 14[…]").

Hate Reported

This data was taken from Table 13 ("Table 13[…]"). Since the FBI records the hate crimes by city, county, and different agencies, the cities and applicable agencies had to be placed into their corresponding counties so the unit of measure between hate crimes and Trump support agreed. If a city resided in more than one county, it was coded for multiple county and placed in the county that contained most of the city's geographic area. If the city was evenly split between counties, then it was coded for multiple county and placed in one of the counties by alphabetical order.

Hate Not Reported

Hate Not Reported was created from the absence of data in Table 14 ("Table 14 […]"). First, cities and counties with missing data were identified. Then they were coded by completeness of their data—if they had incomplete data, and then how many quarters were missing data from non-reporting. Second, the list of counties in Table 14 was checked against the list of all counties in the U.S. Those counties that did not submit any data and were not in any of the FBI's tables were coded as incomplete data, and then as missing 4 quarters of data. If a city submitted hate crime data but its county did not, then the county's number of quarters not reported was noted, but it was included in the "reported" category. *Hate Not Reported* was coded as 0 for "reported" data and 1 for "not reported" data. In the dataset, 768 counties were coded for 1 as "not reported."

Hate Not Reported or Zero

This is the same variable as *Hate Not Reported*, but it also contains counties that reported no hate crimes in their area. "Reported" hate crimes here are nonzero numbers taken from Table 13, and they are coded as 0 ("Table 13 […]"). *Hate Not Reported or Zero* includes "not reported" from the *Hate Not Reported* variable, but also adds counties that reported zero hate crimes in their area; these counties were coded as 1, and there were 2,318 of them in 2015.

Hate Not Reported or Zero was included in the analysis because zeros should be questioned (Nolan 1999). In 2015, Mississippi reported zero hate crimes. Very few counties in Mississippi reported data (3/82 counties), but when counties reported at all, they only reported zero hate crimes. Likewise, Alabama only had six counties report hate crime data, totaling ten hate crimes for 2015, but out of those six counties, three of them were zeros (2015 Hate Crime Statistics). Compare these meager numbers with New Jersey, which reported 330 hate crimes in 2015, or California, which reported 837 (2015 Hate Crime Statistics). In states with histories of racial violence, it is very difficult to take these zeros at face value.

Magnitude of Hate

Since the zeros were taken out of the *Hate Reported* variable and run with the *Hate Not Reported or Zero* variable, the *Hate Reported* variable was run without zeros—called *Magnitude of Hate*. Though underreporting is still a large issue in any measure of hate crime, the *Magnitude of Hate* is meant to correct for some of the questionable zeros.

4.4 Control Variables

County Capacity: Dollars Per Person

This data was taken from the IRS County Tax Data from 2014 (Wong). For the main measure of county capacity, the amount of total tax payments by county was taken from the IRS tax data and divided by the 2015 population by county, which was taken from the ACS 2015 5-year estimates (Wong, Data Access and Dissemination Systems (DADS)). Measures of county capacity are crucial control variables for this analysis because it helps to answer the question of whether counties do not have the resources to gather and submit hate crime data, or if they do have the resources and simply do not care. The other measures of county capacity detailed in the appendix tables are gross amount (the untransformed data from IRS county tax data), and the natural log of the gross amount.

% White, not Latino

This data was taken from the 2015 ACS 5-year estimates, and then divided by total population by county, and multiplied by 100 (Data Access and Dissemination Systems (DADS)). Other measures of race and foreign born are detailed in the appendix, but they were all taken from the ACS 5-year estimates and follow the same transformation procedure as *% White, not*

Latino. This is used because it is reasonable to assume that the racial composition of a county—particularly the white population—might be connected to Trump support and/ or hate crimes in a given county.

Median Household Income

Median household income is measured in dollars, and is taken from the 2015 ACS 5-year estimates. It is not transformed (Data Access and Dissemination Systems (DADS)). Income is included in this analysis as a control because there is controversy over whether Trump voters are wealthy or poor, and it is not well known if income of a county correlates with hate crimes (Casselman 2017; Cerrato 2016; Collingwood 2016; "Kaiser Family Foundation/CNN Working-Class Whites Poll." 2016; Thompson 2016; Yanagizawa-Drott 2016).

Percent Bachelor's Degree or Higher

Whether voters had bachelor's degree or higher was taken from the 2015 ACS 5-year estimates, but was transformed into *Percent Bachelor's Degree or Higher* by dividing by the total population by county and multiplying by 100 (Data Access and Dissemination Systems (DADS)). Bachelor's degree or higher is included as a control because Trump supporters are known to be less educated than other voters, and its inclusion in this analysis will determine whether this holds for counties.

4.5 Descriptive Statistics and Difference in Means Test

Consistent with my hypothesis, both *Hate Not Reported* and *Hate Not Reported or Zero* have a statistically significant lower Trump mean vote share than their respective *Hate Reported* categories.

Table 1: Two-sample T test with Equal Variance

Trump Support (% Vote Share)	Mean Difference from Reported Hate Crimes	Standard Error of Difference	P-Value	T-Score
Hate Not Reported	-1.878	0.6556	0.0042	-2.864
Hate Not Reported or Zero	-11.69	0.6101	0.0000	-19.16

Note: When *Hate Not Reported* = 0, hate crimes are reported (including a reporting of zero hate crimes). When *Hate Not Reported* = 1, hate crimes are not reported. When *Hate Not Reported or Zero* = 0, hate crimes are reported (not including a reporting of zero hate crimes). When *Hate Not Reported or Zero* =1, hate crimes are not reported. A negative difference of means signifies a higher Trump support in counties not reporting hate crimes to the FBI. ***Source****:* An original dataset. Trump support data comes from The New York Times election map and Dave Leip's Atlas of U.S. Presidential Elections (Leip; "Presidential Election Results: Donald J. Trump Wins"). *The Hate Not Reported* and *Hate Not Reported or Zero* variables were created using data from the FBI's UCR data ("Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015").

Chapter 5: Multivariate Empirical Analysis

5.1 Overview

This multivariate empirical analysis includes four models. All models use the same dependent variable: Trump support—vote share of Trump support in the 2016 presidential election. **Model 1** contains a regression of the dependent variable *Trump Support*, and the control variables that will remain constant across all models—*% White, not Latino*, *Median Household Income* in dollars, and *% BA or higher* (Table 2). All of the control variables in **Model 1** were taken from the 2015 ACS 5-year estimates. **Model 1** acts as the foundation for all models because it contains the independent variables that are most commonly associated with Trump support.

Model 2 contains the independent variable of interest, *Hate Not Reported,* and the same controls as **Model 1** (*% White, not Latino*, *Median Household Income,* and *% BA or higher),* in addition to county capacity measured by *$ Per Capita*—total IRS tax receipts divided by ACS 2015 population. County capacity is included in all models except **Model 1** to better understand the question—do counties fail to report because of lack of resources, or because they do not care?

Model 3 and **Model 4** attempt to control for the ambiguity that results from a reporting of zero hate crimes by counties. Zeros are ambiguous because they can indicate that a county did not have any hate crimes during that year, or that they did, but for whatever reason still submitted a report indicating there were zero hate crimes. **Model 3** measures *Hate Not Reported or Zero*, which groups counties that did not report hate crimes to the FBI in 2015 with counties that reported zero hate crimes to the FBI in 2015 ("Table 14 […]"). **Model 3** uses the same control variables that are present in **Model 2**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*.

Model 4 measures *Magnitude of Hate (H>0),* which uses reported hate crimes by county in 2015, though it excludes the counties that reported zero hate crimes ("Table 13 […]"; "Table 14 […]"). **Model 4** uses the same control variables that are present in both **Models 2** & **3**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*.

5.2 Effect of Trump Support on Demographics, Income, and Education (Model 1)

My dependent variable is Trump support measured by vote share in the 2016 general election by county and it is used with all statistical models. **Model 1** runs Trump support against *% White, not Latino*, *Median Household Income*, and *% BA or higher* (Table 2). **Model 1** shows statistically significant positive correlations at the 99.9% confidence level between Trump support and both *% White, not Latino* and *Median Household Income,* and a statistically significant negative correlation at the 99.9% confidence level between Trump support and *% BA or higher.* The positive correlations with demographics and income show that counties that had high Trump support also had higher white (*% White, not Latino*) and wealthy (*Median Household Income*) populations than counties with lower Trump support. Education shows that counties with higher Trump support had less educated (*% BA or higher*) populations then counties with lower Trump support. Trump catered his campaign to white, less educated populations, and both the literature and the results of **Model 1** confirm this. The positive correlation seen with *Median Household Income* may seem counterintuitive at first, but what must be understood is that while people in these areas may be economically *anxious*, they are not undergoing economic *hardship* (Casselman 2017; Silver 2016; "Kaiser […]" 2016).

5.3 Effect of Trump Support on Hate Not Reported (Model 2)

Model 2 contains the independent variable of interest—*Hate Not Reported*. *Hate Not Reported* is the non-reporting of hate crimes that are derived from the FBI's Uniform Crime Reporting (UCR) for 2015 by county ("Table 14 […]"). **Model 2** maintains the controls present in **Model 1**—*% White, not Latino*, *Median Household Income*, and *% BA or higher*—but also controls for county capacity by *$ Per Capita. Hate Not Reported*, *% White, not Latino*, and *Median Household Income* have a statistically significant positive correlation with Trump support at the 99.9% confidence level (Table 2). County capacity (*$ Per Capita*) also has a statistically significant positive correlation with Trump support, but at the 95% confidence level, while *% BA or higher* has a statistically significant negative correlation with Trump support at the 99.9% confidence level (Table 2). *% White, not Latino*, *Median Household Income*, and *% BA or higher* remained very consistent between **Models 1** and **2**.

I found that counties that did not report hate crimes had significantly higher levels of Trump support than those counties that did report hate crimes. These conclusions hold at the 99.9% confidence level even when controlling for county capacity, percent white, median household income, and education (Table 2).

5.4 Effects of Trump Support on Hate Not Reported or Zero (Model 3)

Model 3 measures *Hate Not Reported or Zero*, which groups counties that did not report hate crimes to the FBI in 2015 with counties that reported zero hate crimes to the FBI in 2015

("Table 14 […]"). **Model 3** uses the same control variables that are present in **Model 2**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*. There are statistically significant positive correlations between Trump support and *Hate Not Reported or Zero*, county capacity (*$ Per Capita*), *% White, not Latino, and Median Household Income* all at the 99.9% confidence level, while *% BA or higher* has a statistically significant negative correlation with Trump support at the 99.9% confidence level (Table 2). These results are very similar to both **Models 1** and **2**.

I found that counties that did not report hate crimes or reported zero hate crimes had significantly higher levels of Trump support than those counties that did report hate crimes. These conclusions hold at the 99.9% confidence level even when controlling for county capacity, percent white, median household income, and education (Table 2).

5.5 Effects of Trump Support on Magnitude of Hate (Model 4)

Model 4 measures *Magnitude of Hate (H>0),* which uses reported hate crimes by county in 2015, though it excludes the counties that reported zero hate crimes ("Table 13 […]"; "Table 14 […]"). **Model 4** uses the same control variables that are present in both **Models 2** & **3**—county capacity (*$ Per Capita*), *% White, not Latino*, *Median Household Income*, and *% BA or higher*. This model is best compared to *Hate Reported* in either Appendix tables 1 or 3. There is a statistically significant negative correlation between Trump Support and *Magnitude of Hate* at the 99% confidence level, which is in line with the regression using *Hate Reported* as the primary independent variable, though it is both less negative and less significant. In this way, it mirrors the relationship between *Hate Not Reported* and *Hate Not Reported or Zero*. When the zeros are added to *Hate Not Reported*, it becomes more positive and more significant, just as taking zeros out of *Hate Reported* causes *Magnitude of Hate* to become less negative and less significant. The *Magnitude of Hate (H>0)* conclusions hold even when controlling for county capacity, percent white, median household income, and education (Table 2).

The control variables maintain the same trends as in all the other models and with that of *Hate Reported* (A1 & A13): positive correlation between Trump support and county capacity (*$ Per Capita*), *% White, not Latino*, and *Median Household Income*, while negative with % *BA or higher*. *County* capacity (*$ Per Capita*) is positive, though less so than with *Hate Reported*, and less significant as well. It is important to note that while the signs of the correlation change between the reported variables (*Hate Reported* and *Magnitude of Hate*) and the non-reported variables (*Hate Not Reported* and *Hate Not Reported or Zero*), county capacity (*$ Per Capita*) remains positive and significant for all Models. This gives further evidence that counties *do* have the financial resources to track hate crimes, and that the reason more are not recorded is that, for one reason or another, counties do not care about reporting hate crimes.

5.6 Robustness Check for County Capacity

Appendix tables 1 and 2 (A1-A12) check **Model 2-4's** robustness by using different measures of county-level capacity. Table 2 uses county-level capacity measured by total IRS tax receipts (2014) divided by ACS 2015 population. This is the best measure of county capacity because it transforms this variable into a more manageable number and puts it in context of money per capita. It was chosen as the main measure of county-level capacity for these reasons. The second measure of county-level capacity is the *Gross Amount* (total) in dollars taken directly from the 2014 IRS tax data by county. The third measure is the *Natural log of* [the] *Gross Amount*.

Since the county capacity per capita was discussed previously, A1, A4, A7, and A10 will not be discussed. The correlations between Trump support and both *Hate Reported* and *Magnitude of Hate* remained negative using the *Gross Amount* (A2 and A11), though they are less negative than their counterparts using the per capita (*$ Per Capita*) variable. Neither are significant. *Hate Not Reported* and *Hate Not Reported or Zero* both remained positive, significant at the 99.9% confidence level, and remained very close to the values using the per capita variable (A5 and A8).

The regressions using the *Natural log of Gross Amount* are very similar to the regressions using the *Gross Amount*. The correlations between Trump Support and both *Hate Reported* and *Magnitude of Hate* remained negative, though less so than their regressions using both *Gross Amount* and *Per Capita* (A3 and A12); both remain statistically insignificant. *Hate Not Reported* and *Hate Not Reported or Zero* both remained positive and significant at the 99.9% confidence level (A6 and A9). *Hate Not Reported* shifted in value more than *Hate Not Reported or Zero,* which remained nearly identical to its previous values.

5.7 Robustness Check for Demographics

Appendix Tables 2 and 3 (A13-A24) check **Model 2-4's** robustness by using different measures of demographics. Table 2 uses *% White, not Latino* as the measure of demographics to hold constant because the white population was the most important racial group in electing Trump. Demographics are measured two other ways: *% African American, % Asian*, and *% Latino* in a county, and the percent foreign-born in a county. These measurements are all taken from the ACS 2015 5-year estimates and then divided by population and turned into a percent.

The percentage of the foreign-born population *(% Foreign-born*) was determined in the same way as each of the other demographic percentages.

Since the *% White, not Latino* regressions were discussed earlier, A13, A16, A19, A22 will not be discussed. The regressions using these three main racial groups are important controls, especially considering Trump's rhetoric towards minorities. The correlations between Trump Support and both *Hate Reported* and *Magnitude of Hate* remained negative when controlling for *% African American, % Asian, and % Latino*, though became less significant (A14 and A23). *Hate Not Reported* and *Hate Not Reported or Zero* both remained positive and significant at the 99% and 99.9% confidence levels, respectively (A17 and A20).

The regressions using the percentage of foreign-born are necessary because of Trump's anti-immigration rhetoric. The correlations between Trump Support and both *Hate Reported* and *Magnitude of Hate* remained negative when controlling for *% African American, % Asian, and % Latino*, though *Hate Reported* became more negative and significant, while *Magnitude of Hate* became more positive and less significant (A15, A 24). *Hate Not Reported or Zero* became marginally more positive and maintained its significance at the 99.9% confidence level (A18). *Hate Not Reported* changed in sign from positive to negative and became significant at the 95% confidence level.

Though the main purpose of these tests of robustness is to determine whether the variable of interest remained stable in value and significance using different control variables, it is interesting to note that the percent of foreign-born population in a county is negatively correlated with Trump Support. Additionally, controlling for this variable changed the variables of interest more than any other control in the appendix tables.

5.8 Overall Effects

The variable *Hate Reported*, and its subsequent regressions, cannot be taken at face-value because of non-reporting. It is unclear what the trend would be if every county in the United States submitted complete and accurate hate crime data to the FBI. Because of this, the question: "Can hate crime predict Trump support?" cannot be answered with any confidence at this time. Though it is unclear whether hate crime can predict Trump support, it is clear that the non-reporting of hate crime can predict Trump support.

The models appear very consistent, and the results are robust. **Model 2**—*Hate Not Reported* is positive and significant at the 99.9% confidence level; it is robust for different measures of county-level capacity and demographics. **Model 3**—*Hate Not Reported and Zero* is positive and significant at the 99.9% confidence level; it is robust for different measures of county-level capacity, and demographics. **Model 4**—Magnitude of Hate is negative and significant at the 99% confidence level; it is robust for different measures of county-level capacity and demographics.

Table 2: Trump Support Effects on Models

Trump Support	Model 1	Model 2	Model 3	Model 4
Magnitude of Hate (H>0)				-0.0567** (0.0182)
Hate Not Reported or Zero			4.522*** (0.4697)	
Hate Not Reported		1.942*** (0.4583)		
County Capacity				
$ Per Capita		0.2590* (0.1073)	0.2589* (0.1060)	0.5011* (0.2160)
Demographics				
% White, not Latino	0.5065 *** (0.0123)	0.5148*** (0.0124)	0.4977*** (0.0122)	0.5208*** (0.0262)
Income				
Median Household Income	0.0001*** (2.27E-05)	0.0001*** (2.42E-05)	0.0001*** (2.39E-05)	0.0001*** (4.03E-05)
Education				
% BA or higher	-0.9641*** (0.0301)	-0.9715*** (0.0309)	-0.9106*** (0.0314)	-1.037*** (0.0507)
State Fixed Effects	i	i	i	i

* = p < .05 ** = p < .01 *** = p < .001

Note: The dependent variable in all models is Trump Support measured by vote share in the 2016 general presidential election. Regression coefficients are listed with regression standard errors in parentheses. Model 1 contains controls generally thought to be significant for Trump Support. Model 2 is the Hate Not Reported model, which contains the same controls as Model 1 as well as county capacity per capita. Model 3 is Hate Not Reported or Zero, and contains all the same controls as Model 2. Model 4 is the Magnitude of Hate (Hate Reported >0) along with the same controls as Models 2 and 3. ***Source:*** Trump support data: Leip & "Presidential Election Results: Donald J. Trump Wins". *Magnitude of Hate (H>0), Hate Not Reported* and *Hate Not Reported or Zero* variables derived from Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015". County capacity: IRS 2014 tax data; Demographics, Income, and Education are from ACS 5-year estimates.

Chapter 6: Discussion

6.1 Summary of Results

This paper sought to answer the question: Can non-reporting of hate crimes by county predict Trump support in the 2016 presidential election? In short, the answer was *yes*. The non-reporting of hate crimes was statistically significant at the 99.9% confidence level, while controlling for county capacity, demographics, median household income, and educational attainment (**Model 2**). This means there is a strong correlation between counties that had large amounts of Trump support in 2016, and counties that did not report hate crimes in 2015. The other **Models**—**1**, **3**, **4**—are present to act as validity checks for the structure of the models.

Model 1 is meant as a check against the current literature. Essentially, does this model say the same things that other Trump literature says? It does. While Trump support was difficult to measure using straight demographic data because of conflicting measurements (economic anxiety versus economic hardship), the model does align with what is commonly thought of as characteristics of *places* where Trump did best. Trump did best in areas with a large white population, higher household income—as mentioned before, economic hardship is different than economic anxiety—and less educated populations (Casselman 2017; Silver 2016; "Kaiser Family Foundation/CNN Working-Class Whites Poll." 2016). These are all significant at the 99.9% confidence level.

Models 3 and **4** are checks against the uncertainty of the zeros in the FBI's hate crime data. **Model 3** is added to demonstrate the change in significance if the zeros reported to the FBI are false negatives. **Model 4** is similar to **Model 3** in that it also assumes the zeros reported to the FBI are false negatives. **Model 3** takes the zeros out of the reported hate crime data and adds them to the non-reported variable, while **Model 4** measures the reported hate crime data without the reported zeros. Both models performed as expected. **Model 3** became a more significant (in all values) version of **Model 2**, while **Model 4** became a less significant (in magnitude of hate and county capacity) version of *Hate Reported* (A1).

6.2 Hate Reported

My original interest in this project began with the question: Can hate crimes predict Trump support by county? My hypothesis was that there would be a positive correlation between hate crimes and Trump support by county. The regression between Trump vote share and *Hate Reported* did not substantiate this hypothesis (A1). There was a statistically significant negative correlation between Trump support and hate crimes. However, upon further analysis of the FBI's Table 14 (Hate Crime Zero Data Submitted per Quarter by State and Agency), I noticed that there were quarters of missing data and counties that were not on either table ("Table 13[…]"; "Table 14 […]").

Given the significant missing values in the FBI's data, which is already underreported, I do not believe this result is valid ("Hate Crime Victimization, 2004-2012 - Statistical Tables.", FBI). Because of these missing data, I argue that non-reporting of hate crimes by local governments is a more accurate measure of racism than is the reported hate crimes themselves. Until there is a standardization of hate crime reporting techniques and policies among all states, and the *requirement* that all states submit hate crime reports to the federal government, this data will not be accurate.

6.3 Academic Implications

This research is unique in a few ways. First, it attempts to add to the fast-growing literature attempting to explain Trump. I attempt to connect the racial versus economic anxiety positions and place them in the context of a much larger conversation about minorities, immigration, party identification, and white racist anxiety. I use the non-reporting of hate crimes as a proxy for racism or racial anxiety. Additionally, this paper is unique because it proposes a quantitative measure of racism and attempts to use it to explain voting behavior by county. Most other measures of racial "anxiety" discussed in the literature review are survey data. They ask people to gauge their perceptions of themselves in relation to minority groups or other indirect methods. There is response bias in surveys and no way to determine whether the questions accurately gauge racial sentiments. My data most resembles Michael Tesler's (2013) research on "Old Fashioned Racism" and the Obama administration because he measures racism and its link to partisanship (Tesler 2013). Unlike Tesler's work (2013), I am studying Trump and using hate crime data from every county in the U.S. excluding Alaska. My data is also unique in the realm of hate crime literature because it is quantitative and attempts to tie the non-reporting of hate crimes by county to a measure that is not demographic.

With Trump's election win and the increase in hate crimes, I believe there will be much more data analyses like this one. It will be crucial in the years to come to determine the effect of Trump on hate crimes, race relations in the U.S., and the emergence of the American far-right. To see the effect of Trump on hate crimes in the U.S., there needs to be massive mandatory hate crime legislation implementation, standardization, and reporting among states. The section that follows will describe the specific policy implementations states should take to ensure this.

6.4 Policy Proposal and Implications

The policy and academic implications for this paper are mutually reinforcing. Academic study of hate crimes and larger trends are needed to draw attention to the inconsistent and lacking hate crime legislation. More confident analyses of hate crime data cannot be performed without better data, and better data can only be obtained with increased hate crime legislation and enforcement. The subsections that follow illustrate the main obstacles to proper hate crime reporting.

(1) Victim Reporting

It was estimated that only about 40% of hate crimes in 2012 were reported to police ("Hate Crime Victimization, 2004-2012 - Statistical Tables). For the 60% of crimes that did not get reported to police agencies, the goal should be community outreach and hate crime education. Victims do not report hate crimes for numerous reasons, including but not limited to: lack of knowledge of what constitutes a hate crime; lack of knowledge about victims' rights or available resources; fear of retaliation; fear of being re-victimized by law enforcement (Ahearn 2011). With the creation of a hate crime taskforce, community outreach, and local government elites condemning hate crimes, victims will be more likely to report their attacks (Ahearn 2011).

(2) Initial Police Responder

Police officers and law enforcement administrators alike need to take part in mandatory annual training programs. They should also be required to carry a written definition of what constitutes a hate crime, and the proper procedure for observing and reporting hate crimes. The creation of national hate crime taskforces would be instrumental to increase reporting. They would create and lead the annual hate crime training programs and be an independently functioning body, thereby creating oversight and preventing biased non-reporting.

(3) Secondary Responder and Determination of Bias

Each possible case of biased crime should be reported directly to the hate crime taskforce corresponding to that particular precinct. This way trained experts review each case and make an informed decision of whether bias occurred. Each taskforce is required to stay in contact with precincts under their purview, and precincts are required to stay in contact with their respective taskforces. If precincts are noncompliant, then taskforces will record their noncompliance in a quarterly report that will be sent to their state attorney general as well as the U.S. attorney general.

(4) Participation in National Hate Crime Reporting

Each state's attorney general must publish quarterly hate crime reports on their websites, and send compiled annual reports to the FBI. These steps will only succeed if states are required to submit annual hate crime reports to the FBI and all states pass comprehensive hate crime legislation that use the FBI's definition of hate crime.[3] The most important aspect of this proposal is the creation of hate crime taskforces that have oversight powers. These

[3] The FBI's definition of a hate crime is any "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" (Hate Crimes).

taskforces should have standardized training and personnel should be implemented for a certain proportion of population—twenty taskforces total, each overseeing ~157 counties and the municipalities therein. If comprehensive laws are not passed, the implementation of hate crime taskforces would create a certain measure of accountability among counties and reporting would increase nonetheless.

6.5 Combating Underlying Racism and Racial Anxiety

Even if hate crime policies are implemented, that will not alter the underlying reasons people commit hate crimes, or the racist superiority that led to county non-reporting to begin with. If the basis for my proposed mechanisms are correct, then understanding how to reach the racially and anxious white population is important. More cultural education in schools that feature open discussions of race, rather than stifling these discussions in favor of colorblindness would be a start. Mandatory racial anxiety seminars given at workplaces, or free counseling sessions that focus on racial anxiety would also be helpful.

More research needs to be done to determine what methods help ease racial anxiety without fostering more resentment because of those methods. There is going to be no single answer to this problem. We cannot simply ask people not to be racist; most people's racism is subconscious and out of their control. Feelings of racial resentment have been simmering in white America since the civil rights era and before, but especially since the realignment of 1980, the events of 2001, and the presidency of Barack Obama. Trump's rhetoric spoke to this resentment, and his candidacy has shed light on racial tensions that America has tried to bury for a generation. Trump is the candidate of white backlash; what we must do now is figure out how to combat that.

Chapter 7: Racial and Ethnic Politics After Trump

7.1 Predicting the Unpredictable

Trump is an unpredictable president. He continues to flip-flop on policies, and he views every encounter as an opportunity to "win" at all costs (Brams 2017). Since Trump took office, he has signed 16 executive orders (Trump). Some of these include rolling back Obamacare, fulfilling his campaign promise to build a wall along the U.S.-Mexico border, cutting the funding for sanctuary cities, banning visas for six majority Muslim countries—Iran, Libya, Somalia, Sudan, Syria, Yemen—and creating a task force to reduce illegal immigration, drug trafficking, and violent crimes (Trump). The first travel ban was blocked by a federal judge, but the revised version, which also suspends refugee resettlement, has not been blocked. Trump has also signed a memorandum banning U.S. funding of international NGO's that provide abortions (Trump). Between Trump's slew of executive orders, memoranda, and filling his cabinet with wealthy business tycoons who seem to have little to no governmental experience, Trump has proven himself to be the unconventional and unpredictable candidate (Berman 2017).

While the travel ban and cutting abortion funding have grabbed people's attention, the task force to reduce illegal immigration, drug trafficking, and violent crimes is also troubling. Given Jeff Sessions's history of blatantly racist, anti-black remarks and his staunch opposition to both legal and illegal immigration, he is an unsettling choice as Attorney General and does not bode well for increased hate crime legislation or support (Berman 2017, Farrell 2016).

7.2 Rhetoric

Donald Trump is notorious for his rhetoric—mainly his anti-minority, anti-immigration rhetoric. However, Trump's rhetoric represents a break from political correctness that has been present in political and social culture since the 1970s-1980s. His supporters see him as genuine and "just telling it like it is," but the loss of political correctness may have far broader implications (Farrell 2016). If reports surrounding increased amounts of hate crime following the election are true, then people who have always been racist, but prevented by social norms from showing it publicly, have just witnessed the election of a man who has made overtly racist comments about minorities and surrounded himself with people who are even more racist (Farrell 2016). The knowledge that their views are more widely shared than they thought before, or the fact that a political elite, celebrity, and now president seems to share their racist sentiments could embolden such people to act on their beliefs when they previously would not have.

Can Trump be blamed for this violence? Recent judicial rulings seem to indicate that he can be. A federal judge in Kentucky recently ruled that Trump's rhetoric incited violence at one of his campaign rallies last year, thereby nullifying his first amendment right of free speech (Blake). A different federal judge from Hawaii recently rejected Trump attorney's argument that the travel ban executive order should be considered apart from Trump's previous comments regarding the initial purpose of the ban—to target Muslims (Blake). These rulings indicate that judges and arguably rally goers are taking his words at face value. How many other people are taking Trump's rhetoric at face value and internalizing it? I believe proving this last question, and the extent to which elite rhetoric against minority population(s) influences people's actions towards those groups will be of the utmost importance.

It will take years to fully understand the implications of a Trump presidency on the race relations in the United States, but from what can be seen so far, Trump seems to be keeping his election promises, and that is bad for racial equality.

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Appendix

Appendix Table 1: Robust to Different Measures of County-Level Capacity

Trump Support	**A1**	**A2**	**A3**	**A4**	**A5**	**A6**	**A7**	**A8**	**A9**
Hate Reported	-0.0955*** (0.0188)	-0.0496 (0.0259)	-0.0124 (0.0187)						
Hate Not Reported or Zero				4.522*** (0.4697)	4.200*** (0.4761)	1.772*** (0.5048)			
Hate Not Reported							1.942*** (0.4583)	1.806*** (0.4573)	1.772*** (0.4414)
County-Level Capacity									
$ Per Capita	0.4925*** (0.1186)			0.2589* (0.1060)			0.2590* (0.1073)		
Gross Amount		-2.97E-07* (1.35E-07)			-3.64E-07*** (9.43E-08)			-4.88E-07*** (9.40E-08)	
Natural log of Gross Amount			-2.508*** (0.1713)			-2.027*** (0.1568)			-2.246*** (0.1422)
Demographics									
% White, not Latino	0.4966*** (0.0160)	0.4868*** (0.0162)	0.4261*** (0.0160)	0.4977*** (0.0122)	0.4860*** (0.0124)	0.4537*** (0.0123)	0.5148*** (0.0124)	0.4983*** (0.0126)	0.4584*** (0.0124)
% African American									
% Asian									
% Latino									
% Foreign-born									
Income									
Median Household Income	0.0001*** (2.71E-05)	0.0002*** (2.56E-05)	0.0002*** (2.51E-05)	0.0001*** (2.39E-05)	0.0001*** (2.25E-05)	0.0002*** (2.27E-05)	0.0001*** (2.42E-05)	0.0001*** (2.28E-05)	0.0002*** (2.26E-05)
Education									
% BA or higher	-1.010*** (0.0345)	-0.9714*** (0.0342)	-0.8234*** (0.0342)	-0.9106*** (0.0314)	-0.8742*** (0.0309)	-0.7973*** (0.0307)	-0.9715*** (0.0309)	-0.9226*** (0.0307)	-0.8008*** (0.0306)
State Fixed Effects	i	i	i	i	i	i	i	i	i

* = p < .05   ** = p < .01   *** = p < .001

Note: This table describes the independent variables contained in models 2 and 3; regressions were run to determine the breadth of robustness to different measures of county-level capacity while controlling for demographics, income, and education. The table shows robust results for *Hate Not Reported or Zero* and *Hate Not Reported* across all three measures of county capacity. ***Source:*** Trump support data: Leip & "Presidential Election Results: Donald J. Trump Wins". *Magnitude of Hate (H>0), Hate Not Reported* and *Hate Not Reported or Zero* variables derived from Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015". County capacity: IRS 2014 tax data; Demographics, Income, and Education are from ACS 5-year estimates.

Appendix Table 2: Robust to Different Measures of County-Level Capacity			
Trump Support	**A10**	**A11**	**A12**
Magnitude of Hate (H>0)	-0.057** (0.0182)	-0.0310 (0 .0242)	-0.0090 (0.0186)
County-Level Capacity			
$ Per Capita	0.5011* (0.2160)		
Gross Amount		-1.64E-07 (1.29E-07)	
Natural log of Gross Amount			-2.232*** (0.3218)
Demographics			
% White, not Latino	0.5208*** (0.0262)	0.5092*** (0.0268)	0.4508*** (0.0272)
% African American			
% Asian			
% Latino			
% Foreign-born			
Income			
Median Household Income	1.44E-04*** (4.03E-05)	1.94E-04*** (3.65E-05)	2.53E-04*** (3.63E-05)
Education			
% BA or higher	-1.037*** (0.0507)	-0.9906*** (0.0481)	-0.8653*** (0.0503)
State Fixed Effects	i	i	i

* = p < .05 ** = p < .01 *** = p < .001

Note: This table describes the independent variable contained in model 4; regressions were run to determine the breadth of robustness to different measures of county-level capacity while controlling for demographics, income, and education. ***Source:*** Trump support data: Leip & "Presidential Election Results: Donald J. Trump Wins". *Magnitude of Hate (H>0), Hate Not Reported* and *Hate Not Reported or Zero* variables derived from Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015". County capacity: IRS 2014 tax data; Demographics, Income, and Education are from ACS 5-year estimates.

Appendix Table 3: Robust to Different Measures of Demographics									
Trump Support	**A13**	**A14**	**A15**	**A16**	**A17**	**A18**	**A19**	**A20**	**A21**
Hate Reported	-0.0955*** (0.0188)	-0.0638** (0.0193)	-0.1040*** (0.0218)						
Hate Not Reported or Zero				4.522*** (0.4697)	4.135*** (0.4756)	4.605*** (0.5659)			
Hate Not Reported							1.942*** (0.4583)	1.459** (0.4635)	-1.183* (0.5424)
County-Level Capacity									
$ Per Capita	0.4925*** (0.1186)	0.7039*** (0.1183)	0.5164*** (0.1350)	0.2589* (0.1060)	0.4849*** (0.1077)	0.2030 (0.1268)	0.2590* (0.1073)	0.4863*** (0.1088)	0.2162 (0.1280)
Gross Amount									
Natural log of Gross Amount									
Demographics									
% White, not Latino	0.4966*** (0.0160)			0.4977*** (0.0122)			0.5148*** (0.0124)		
% African American		-0.4957*** (0.0186)			-0.4766*** (0.0141)			-0.4867*** (0.0144)	
% Asian		-1.118*** (0.1194)			-1.037*** (0.0937)			-1.156*** (0.0938)	
% Latino		-0.2255*** (0.0163)			-0.2451*** (0.0147)			-0.2480 *** (0.0149)	
% Foreign-born			-0.7348*** (0.0480)			-0.7275*** (0.0452)			-0.8043*** (0.0451)
Income									
Median Household Income	0.0001*** (2.71E-05)	0.0001*** (2.72E-05)	0.0003*** (3.06E-05)	0.0001*** (2.39E-05)	0.0002*** (2.45E-05)	0.0004*** (2.76E-05)	0.0001*** (2.42E-05)	0.0002*** (2.48E-05)	0.0004*** (2.80E-05)
Education									
% BA or higher	-1.010*** (0.0345)	-0.9981*** (0.0362)	-1.050*** (0.0391)	-0.9106*** (0.0314)	-0.9094*** (0.0328)	-1.001*** (0.0372)	-0.9715*** (0.0309)	-0.9569*** (0.0326)	-1.072*** (0.0367)
State Fixed Effects	i	i	i	i	i	i	i	i	i

* = p < .05 ** = p < .01 *** = p < .001

Note: This table describes the independent variables contained in models 2 and 3; regressions were run to determine the breadth of robustness to different measures of demographics while controlling for county capacity, income, and education. The table shows robust results for *Hate Not Reported or Zero* and *Hate Not Reported*. ***Source:*** Trump support data: Leip & "Presidential Election Results: Donald J. Trump Wins". *Magnitude of Hate (H>0), Hate Not Reported* and *Hate Not Reported or Zero* variables derived from Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015". County capacity: IRS 2014 tax data; Demographics, Income, and Education are from ACS 5-year estimates.

Appendix Table 4: Robust to Different Measures of Demographics			
Trump Support	**A22**	**A23**	**A24**
Magnitude of Hate (H>0)	-0.057** (0.0182)	-0.0408* (0.0177)	-0.0390 (0.0200)
County-Level Capacity			
$ Per Capita	0.5011* (0.2160)	0.6184** (0.2051)	0.6381** (0.2329)
Gross Amount			
Natural log of Gross Amount			
Demographics			
% White, not Latino	0.5208*** (0.0262)		
% African American		-0.4783*** (0.0295)	
% Asian		-0.6710*** (0.1264)	
% Latino		-0.3517*** (0.0264)	
% Foreign-born			-0.9204*** (0.0596)
Income			
Median Household Income	0.0001*** (4.03E-05)	0.0002*** (3.99E-05)	0.0003*** (4.33E-05)
Education			
% BA or higher	-1.037*** (0.0507)	-1.069*** (0.0504)	-1.089*** (0.0542)
State Fixed Effects	i	i	i

* = p < .05 ** = p < .01 *** = p < .001

Note: This table describes the independent variable contained in model 4; regressions were run to determine the breadth of robustness to different measures of demographics while controlling for county-level capacity, income, and education. ***Source:*** Trump support data: Leip & "Presidential Election Results: Donald J. Trump Wins". *Magnitude of Hate (H>0), Hate Not Reported* and *Hate Not Reported or Zero* variables derived from Table 14: Hate Crime Zero Data Submitted per Quarter by State and Agency, 2015". County capacity: IRS 2014 tax data; Demographics, Income, and Education are from ACS 5-year estimates.