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Political Parties and Hate Crimes: Empirical Evidence from the United States

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Abstract

This paper evaluates the relationship between political parties and hate crimes in the US, based on the empirical models, considering a panel data with 47 states from 1997 to 2019. Results show that a Democratic president is correlated with fewer crimes of hate if compared with a Republican. Such a result might occur due to different public policies according to the political party in power. Results also show that Democratic governors have a positive correlation with hate crimes, but further exercises show that this is only true for Southern states. In non-Southern states, Democratic governors are negatively correlated with hate crimes.

Keywords: hate crimes, political parties, causes of crime, GMM-System

1. Introduction

A hate crime is, as defined by the Federal Bureau of Investigation (FBI), 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, 2021). Motivated by bigotry and bias, these crimes may occur in many ways such as vandalism, arson, and even murder. Beyond intolerance and prejudice, hate crimes can have economic, political, and social motivations.

Hate crimes have some characteristics that differentiate them from other types of crime, such that understanding its possible determinants is an important issue to effectively confront them. First, hate crimes might affect their victims differently. As indicated by Craig (2002), victims of hate crimes may experience higher levels of posttraumatic stress and need more time to overcome their experience, if compared to victims of non-bias crimes. Apart from these consequences, when a hate crime is committed, it sends a message to every member of the victim's group, affecting all of them negatively (Levin & Mcdevitt, 1993). Literature shows that, compared to similar crimes, hate crimes cause greater harm due to their negative externalities. Psychological harms to members of a targeted group, the difficulties to hide one's identity (in order not to be a victim of hate crimes in certain areas), and monetary losses due to fewer market connections between groups are some of the possible explanations (Dharmapala & Garoupa, 2004; Gan et al., 2010).

Existing literature in Economics, Social Psychology, and Criminology shows, through theory and evidence, possible determinants to hate crime. Economic literature explains how factors such as poverty, inequality, law enforcement, and income might influence the number of hate crimes. Economic theories also model hateful behaviour, in which some individuals have a gain in utility when victims of a determined group are worse off (Gale et al., 2002; Medoff, 1999; Dharmapala & Garoupa, 2004). In Social Psychology and Criminology, literature shows that hate crimes can be seen through the minority threat theory, in which a major group feels threatened whenever a minor group has a relative raise in terms of economic, political, cultural, or demographic determinants (Blalock, 1967; Rees et al., 2009; King et al., 2009). Hate crimes are seen, through these lenses, as a tool to face such threats to the major group. Indeed, empirical evidence shows that economic rivalries between groups and a higher proportion of minorities in a certain area might raise the number of hate crimes, as well as raise the voting in far-right candidates (Jacobs & Wood, 1999; Giles & Buckner, 1993; Disha et al., 2011). On the other hand, there is evidence of a growing online structure supporting far-left wing extremism, such as anarcho-socialism groups (Finkelstein et al., 2020). Extremism – whether to the left or the right of the political spectrum – is connected to more hate violence.

Studies have also shown that political determinants are an important way to understand hate crimes. Political theories on hate crimes see the grievances toward certain groups as a root of biased crimes. The political environment can be seen as a tool to greater visibility and legitimacy of these grievances, which can influence possible hate crime perpetrators (Green et al., 2001). Evidence shows that extreme ideologies discourses (Glaeser, 2005), support to more extreme politicians (REES et al., 2019), and higher visibility and legitimacy of hate speech (Koopmans & Olzak, 2004; Müller & Schwarz, 2020) are related to more hate crimes. Specifically, in terms of the presidency, Edwards and Rushin (2018) present a positive relationship between electing Donald Trump to the U.S. presidency and an increase in hate crimes, such that this effect started during the elections. Bursztyn et al. (2020) shows that a surprising election of a politician such as Trump can result in a change of social norms.

Thus, evidence shows that politicians in power, especially more extreme ones, may affect the number of hate crimes. In a context of increasing polarization, mainly driven by social issues and by Republican politicians getting more extreme than Democrats (Canen et al., 2020; Moskowitz et al., 2019), it raises the question of whether different political parties in power affect hate crimes differently. However, it is important to stress that, although recent evidence on hatred focuses on Republican politicians, this is not an issue that is only historically connected to the GOP. Not only was the Democratic Party formerly a representation of slave-owners' interests during its early years, but, even during the previous century, a group of southern Democrats opposed the Civil Rights Act of 1964. Thus, due to several peculiarities of these political parties, an empirical analysis is necessary to determine possible differences concerning political parties in power and hate crimes.

Hate crime data provided by the Federal Bureau of Investigation (FBI) shows different trends according to which change occurs in the presidency. By analysing hate crime rates from 1997 to 2019, we can see that, whenever a Republican succeeds a Democrat, there is a rise in hate crimes. Although the rise in 2001, when George W. Bush assumed the presidency, was partially due to the terrorist attacks on September 11 (Disha et al., 2011), this trend has also occurred when Donald Trump was elected president, in which hate crimes increased 16.0% in 2017. The opposite has happened during this period when Barack Obama, a Democrat, was elected president: in 2009, the hate crime rate decreased 18.5%. Obama's presidency was also a period in which there was a lower rate of hate crimes (an average of 19.83 hate crimes per million people per year) compared to George (26.89) and Donald Trump's (22.9) Republican mandates. Even though Clinton's second mandate (which was analysed in this obtained data) registered higher hate crime rates (28.99) than Bush's mandate, a possible important factor was that the latter reflected a decline in general crimes rate, whose patterns are reflected in hate crimes. Additionally, during all presidential election years, an increase in hate crimes has occurred, which might reflect inflammatory rhetoric during political campaigns (Edwards & Rushin, 2018).

However, Lin (2007) was one of the first researchers that showed empirical evidence for a relationship between democracy and crime. The author shows that compared to non-democratic governments, governments punish major (minor) crimes with more (less) severity and, consequently, this crime rate is lower (higher). In other words, the effect of democracy on crime is negative for serious crimes like murder and positive for minor crimes like robbery, for example.

In this context, we use an empirical approach to analyse the relationship between political parties in government and hate crime rates in the United States by constructing panel data with 47 states from 1997 to 2019. Additionally, we verify if there is a positive relationship between hate crimes and presidential election years. We also control for other economic and sociodemographic variables that are found in literature, such as those used by Disha et al. (2011), Edwards and Rushin (2018), Gale et al. (2002), King et al. (2009), and Ryan and Leeson (2011). These controls are the unemployment rate, income, black population, young population, state government spending on police protection, violent crime rate, and the population covered by the hate crime statistics.

This work follows the literature that empirically analyses hate crime determinants. In terms of political determinants, existing papers have analysed the importance of access to hate speech (Müller & Schwarz, 2020), support to far-right politicians (Rees et al., 2019), and the election of a given president (Edwards & Rushin, 2018) in terms of raising hate crimes. Considering the polarization of American political parties in terms of social issues (Moskowitz et al., 2019), we contribute to the hate crime and political economy literature by empirically analysing a possible direct relationship between hate crimes and political parties in power.

The paper is organized as follows. Beyond this Introduction in Chapter 1, we present a literature review on hate crimes and their main theories and evidence in Chapter 2. Chapter 3 presents the obtained data and the empirical approach. In Chapter 4, we discuss the results and further perform robustness tests. Concluding remarks are presented in Chapter 5.

2. Literature Review

2.1 Economic Theories

The search for the main determinants of conflicts among groups and, more specifically, of hate crimes raised the formulation of theories that aim to explain the origin of such conflicts. Whether in economic literature or areas such as Criminology and Social Psychology, several authors aim to understand which economic, social, geographic, and psychological factors are determining hate crimes.

In Economics, theories regarding hate crimes are influenced by classical models of crime and violence, particularly those formulated by Gary Becker. The model presented in Gale et al. (2002), for example, embodies hate crimes to the model of Becker (1981) on altruism and envy in families. For Gale et al. (2002), those who commit hate crimes have a maleficent intention, in the same way as the envious behaviour modelled by Becker. Thus, there is a motivation to let the victim worse off, in which the offender has a raise in utility whenever a member from a different group loses welfare.

Dharmapala and Garoupa (2004) extend the analysis of hate crimes to a previously unobserved aspect: social losses caused by those crimes. Choosing victims in a biased way not only causes harm due to the crime itself but also causes additional harm to the members of the discriminated group (Levin & Mcdevitt, 1993). Accordingly, their result shows that a crime disproportionately targeting a certain group causes greater harm than crimes in which victims are randomly chosen.

It is also possible to find literature that aims to empirically answer if economic factors influence hate crimes. In a previously cited paper, for example, Gale et al. (2002) also tries to empirically find evidence to the introduced model. Using FBI hate crimes data, they find that only the unemployment rate and Jewish proportion have positive coefficients. Other than that, it shows that the higher the black to white household incomes, the higher tends to be the number of hate crimes committed by white people against black people. In a similar way, Medoff (1999) shows that higher wages negatively impact hate crimes, while higher unemployment rates and young population rates have a positive impact. Religion and law enforcement spending, on the other hand, do not have statistically significant coefficients.

The study by Green et al. (1998) finds a different result, in which economic factors have no relationship with crimes against minorities. The paper analyses racially motivated crimes targeting minorities using data from New York between 1987 and 1995. Results show that the unemployment rate has a statistically insignificant coefficient, as well as poverty rate, median income, and the ratio of white to the non-white unemployment rate. Indeed, the paper points out that this type of crime tends to occur more in predominantly white areas and where a minority in-migration occurred. Entorf and Lange (2019) find similar results by observing hate crimes against immigrants in Germany. They find that these crimes have a higher incidence in regions with previously lower levels of immigrants and that receive a greater number of asylum seekers. Economic factors, on the other hand, do not explain hate crimes.

2.2 Social Psychology and Criminology Theories

Generally, the economic approach to hate crimes uses a rational aspect of criminal behaviour, in which costs and benefits to criminal activities are observed to maximize the criminal’s utility. However, this is not the only approach to be found in hate crime literature. Criminological and Social Psychological studies bring their approaches to these crimes, in which the main theories emphasize the minority threat. In these theories, a majority group would feel threatened by the rise of the minority group in its region, whether due to social, psychological, or economic factors. In that regard, a classical explanation about group relationship is found in Blalock (1967), that shows how a growing minority is seen as a threat and as a greater competition to the majority group, resulting in more discrimination.

Similarly, Rees et al. (2019) point out that the perception that some out-groups might threaten a group’s status or culture is the major psychological factor that explains certain negative attitudes toward groups. Adapting to the racial conflict case, King et al. (2009) addresses the racial threat thesis, such that the growth of minority race population might be seen as a threat to the elites and major populations. Major groups can react to this threat in many ways, such as biased attitudes, voting for right-wing groups, and broader state control (King et al., 2009). In criminology, strain theory is adapted to the hate crimes case. Such an approach shows how crime results from the difference between financial and material success and the available means to this end. Thus, people from different groups would raise competition for jobs and resources, threatening economic stability and resulting in hate crimes (Hall, 2014).

These results are generally found in the literature, pointing out that the presence of minority groups is positively related to hate crimes. Jacobs and Wood (1999), for example, address racial conflicts and how they might result in interracial homicides. To represent economic rivalries, the authors use the ratio of black to the white unemployment rate. Through a Tobit model, they find that cities with greater economic competition between races and with a black mayor have more white killings of blacks.

Disha et al. (2011) investigates the determinant of hate crimes against Arabs and Muslims in the United States and observe dynamic changes after the terrorist attacks on September 11, 2001. Using FBI hate crimes data between 2001 and 2002, they observe a significant increase in hate crimes against Arabs and Muslims after 9/11, but the main determinants remained the same. They find that places with a higher concentration of Muslims and Arabs would have higher crimes such as these.

2.3 Politics, Ideology, and Polarization

Beyond determinants and theories from Economics, Social Psychology, and Criminology, there are also political theories on hate crimes. These theories see the root of hate crimes motivation on grievances toward certain groups. According to Green et al. (2001), such grievances might be based on fear, frustration, or disdain. In addition to grievances, those who commit hate crimes also act based on political opportunity structure, defined in other words as the "availability of channels to express grievances, the legitimacy of grievances within public and political discourse and the likelihood of prevention or punishment of hate-motivated crimes" (Green et al., 2001, p. 488). The political environment, therefore, may be an opportunity to express grievances and to influence the population.

There is evidence that political discourses and elections can influence the population's behaviour. As pointed out by Bursztyn et al. (2020), a surprising election of a politician can result in a change of social norms. They show that the election of Donald Trump in the United States increased the propensity of individuals to express xenophobic views publicly, decreasing the negative sanctions to previously stigmatized views. Edwards and Rushin (2018) use American hate crime data between 1992 and 2017 to evaluate if electing Donald Trump to the U.S. presidency increased hate crimes. Such a hypothesis is confirmed by the results, which show how counties that voted for Trump by wider margins experienced larger increases in reported hate crimes. They discuss a theory in which, by electing Trump, there was a validation of his inflammatory rhetoric to the eyes of those who commit hate crimes.

Likewise, Rees et al. (2019) indicate that, in Germany, support to far-right parties and right-wing hate crimes are indicated as behavioural forms of political extremism. They show that both factors have similar psychological and social structures, signalling that support to far-right politicians might be an additional indicator of areas with high extremism risk. Far-left groups and intellectuals, on the other hand, have a significant influence on the so-called "new antisemitism", according to Stauber (2008), in a movement that is occurring particularly in the United States and Europe. Evidence presented by Taguieff (2004) shows that anti-Israel propaganda, like those by far-left groups, might influence and incite violence. Koopmans and Olzak (2004) and Müller and Schwarz (2020) present additional evidence on how extreme discourse visibility positively influences hate crimes.

Increased animosity between groups is an important factor to be observed, in which its link to politics may be seen through polarization. Increasing polarization between Republicans and Democrats has occurred during the last years, especially due to ideological polarization between the two parties (Canen et al., 2020). Moskowitz et al. (2019), in addition, shows that part of this difference between parties arises from polarization in social issues, whereas economic issues are less important. Moreover, there is evidence of asymmetric polarization, in which Republican politicians are becoming ideologically more extreme than Democrats (Moskowitz et al., 2019).

Therefore, it seems that Republican and Democrat politicians have different views on social issues, which can induce different policies toward these questions. Literature shows that different political parties, depending on their ideologies, may have different impacts on crimes. Loureiro et al. (2018), for example, consider the case for homicides and political parties in Brazil. By analysing panel data for 27 Brazilian states over 32 years, they show that, when the Workers' Party was controlling the government, there was an increase in homicide rate when compared to other political parties.

As political determinants are, as presented, important factors concerning hate crimes, and considering the polarization on social issues is a growing concern, it is important to address the question of whether political parties affect hate crime rates differently. Thus, this study aims to empirically analyse if there is a relationship between Democrats or Republicans in government and hate crimes. Considering the effect of polarization and political discourses on hate crimes, it also analyses whether presidential election years have any impact on hate crime rates.

3. Data and Empirical Approach

3.1 Data

Hate crime data for the current analysis comes from the FBI's Hate Crimes Statistics Reports, created after the Hate Crime Statistics Act of 1990. The law required the Attorney General to collect data "about crimes that manifest evidence of prejudice based on race, religion, sexual orientation, or ethnicity" (FBI, 2004). In 2009, the Matthew Shepard and James Byrd Jr. Hate Crimes Prevention Act expanded the definition of hate crimes, including those "crimes motivated by the victim's actual or perceived gender, gender identity, sexual orientation, or disability" (Cheng et al., 2013, p. 762). Hate crime incidents are voluntarily reported by local law enforcement agencies. Thus, reported data varies by state and year, which makes it incomplete. We further address this issue by collecting data on the population covered by the Hate Crime Statistics Report from the Uniform Crime Reporting (UCR) program.

Figure 1 shows the rate of hate crime incidents per million people in the United States from 1997 to 2019. Data is separated according to the president in each period, as well as his political party. First, we can see that there is a hike in the number of hate crimes in 2001. This increase in hate crime rate was partially due to the terrorist attacks on September 11, 2001. Disha et al. (2011) shows that there was a sharp increase in hate crimes against Arabs and Muslims after 9/11. This rise in the hate crimes rate also coincides with the first year of George W. Bush as president of the United States. Second, we can see a decrease in the rate of hate crimes after Barack Obama's election to the presidency, in which the rate went from 26.44 hate crime incidents per million population in 2008 to 21.56 in 2009 (-18.5%). On the other hand, after Donald Trump was elected president, there was an increase in the rate of hate crimes, from 19.42 hate crimes per million in 2016 to 22.52 in 2017 (+16.0%), in Trump's first year as president. This raises the question of whether a president's party is a determinant of hate crimes due to its lower rates during the Democratic presidency compared to Republican mandates. Third, the graphic also shows that, during years of a presidential election (2000, 2004, 2008, 2012, and 2016 during the analysed data), there is an increase of hate crimes compared to the previous year. Thus, we also analyse whether there is a positive relationship between hate crimes and presidential election years since inflammatory rhetoric during political campaigns and expectations of presidential electoral victory might induce more violence (Edwards & Rushin, 2018; Kalmoe & Mason, 2019).

To investigate a possible relationship between political parties in the presidency and hate crimes, we construct panel data with 47 states from 1997 to 2019, in which this period is used due to the availability of data for the variables used in the model. We aggregate the FBI's hate crime data to the state and year level using the rate of hate crimes per million population as the outcome of interest (*hate_crime*). It is used as the dependent variable in this study. To determine whether Democrats in the presidency influence hate crimes differently if compared to Republicans, we create a dummy variable (*pres_dem*) that equals one if there is a Democratic president during that year and zero otherwise. To check if presidential election years have a different impact on hate crimes compared to other years, we also create a dummy variable (*elections*) that is equal to one in presidential election years and zero otherwise. A third dummy variable (*gov_dem*) controls for Democratic governors to determine whether Democratic state governors have a different impact on hate crimes compared to Republicans and Independents. These three dummies are used as the main independent variables in this study.

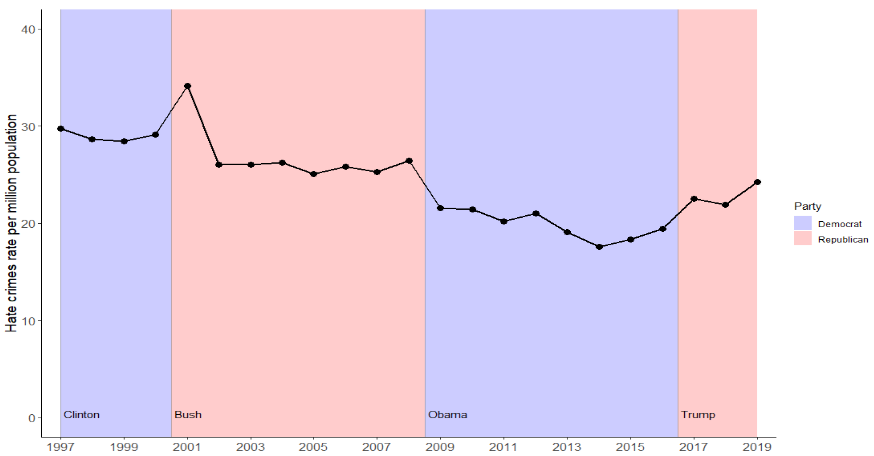

Figure 1. Hate crimes rate per million population in the U.S.

Source: FBI (2019), Prepared by the authors.

We control for a variety of economic and sociodemographic variables used in literature that might influence the rate of hate crimes. Among these controls is the unemployment rate (*unemployment*), which is mostly shown in literature as positively correlated to hate crimes. Another economic control is the real income per capita (*gdp_pc*) in 2019 dollars, that has ambiguous results in hate crime literature in terms of connections to hate crime rates. The state population that is African American (*black_pct*) is one of the sociodemographic variables. According to the minority threat theory, a higher prevalence of members of a victim group may result in a higher rate of hate crimes. On the other hand, a higher proportion of members of a minority may induce a lower probability of victimization (DISHA et al., 2011). We also follow Disha et al. (2011) and use the percentage of state population aged 15 to 24 (*young_pct*), expecting that younger individuals commit proportionately more hate crimes.

State government spending devoted to police protection (*police_spending*) is also used as a control. According to Ryan and Leeson (2011, p. 257), it "accounts for potential differences in criminal activity across states and over time resulting from differences in citizens' protection against crime." In addition, we use the violent crime rate (*violent_crime*), which includes homicide, rape, robbery, aggravated assault, property crime, burglary, larceny, and motor vehicle theft. We use this following Disha *et al*. (2011), which points out that hate crimes might reflect general patterns of criminal activities. Finally, we also use the percentage of the state population that is covered by the UCR's hate crimes statistics each year. Thus, we address the problems that arise due to imperfect reports, accounting for changes in coverage share (Ryan & Leeson, 2011; Edwards & Rushin, 2018; Gale et al., 2002).

We get data for these variables from the FBI's Uniform Crime Reporting Statistics, the U.S. Bureau of Labour Statistics, the Bureau of Economic Analysis, and the United States Census Bureau. We collect these variables for every year and state in the sample. Table 1 presents the summary statistics for the independent and dependent variables.

Table 1. Summary statistics

Variable	**Definition**	**Mean**	**S.D.**
hate_crime	Hate crime rate per million inhabitants, by state	24.61	17.48
pres_dem	Equals one if the United States was governed by a Democrat during the year, and zero otherwise	0.52	0.50
elections	Equals one if a presidential election occurred during the year, and zero otherwise	0.22	0.41
gov_dem	Equals one if the state was governed by a Democrat during the year, and zero otherwise	0.42	0.49
unemployment	Unemployment rate	5.29	1.93
gdp_pc	Gross Domestic Product per capita, in 2019 dollars, by state	54770.76	11030.37
black_pct	Black population as a share of the state population	0.10	0.09
young_pct	Population aged 15 to 24 as a share of the state population	0.14	0.01
police_spending	Percentage of state government expenditures on police protection	0.03	0.01
violent_crime	Violent crime rate per 100,000 inhabitants, by state	400.02	175.80
popshare	Population covered by UCR's Hate Crime Statistics report	0.88	0.20

Source: Prepared by the authors.

3.2 Empirical Approach

To investigate possible correlations to hate crime, we first construct an empirical model based on the GMM-System approach to dynamic models of panel data based on Arellano and Bond (1991), Arellano and Bover (1995) and Blundell and Bond (1998):

$$\ln(hate_{crime_{i,t}}) = \alpha\ln(hate_{crime_{i,t-1}}) + \gamma P_t + \delta E_t + \eta G_{i,t} + \beta_1\ln(Economic_{i,t}) + \beta_2\ln(Sociodemographic_{i,t}) + \beta_3 ln(Popshare_{i,t}) + \nu_{i,t}\ for\ i = 1,\dots,N;\ t = 1,\dots,T \quad (2)$$

Where *hate_crime*$_{it}$ is the hate crime rate per million population in state i and year t. P_t, E_t, and $G_{i,t}$ are dummies for Democratic presidents, presidential election years, and Democratic state governors, respectively. *Economic*$_{i,t}$ and *Sociodemographic*$_{i,t}$ are economic and sociodemographic controls. *Popshare* represents the share of the state's population that is covered by the UCR's hate crime statistics. The model also includes the lagged hate crimes rate (*hate_crime*$_{i,t}$) and $\nu_{i,t} = \mu_i + \epsilon_{i,t}$, a vector of error terms. The disturbance term, $\nu_{i,t}$, has two components: μ_i represents the fixed effects and $\epsilon_{i,t}$, the idiosyncratic shocks. These two components are orthogonal, and both have an expected value of zero. In this model, α might capture a causal effect of criminal inertia in terms of hate crimes, which represents a temporal persistence.

Dynamic models of panel data are widely used in the empirical literature on the Economics of Crime. Examples can be found in papers such as those by Fajnzylber et al. (2002), Choe (2008), and Loureiro et al. (2018). In terms of hate crimes, a dynamic model is used by Mulholland (2013) to check the effect of white supremacist groups on hate crimes. The author uses hate crime rates as a dependent variable and its lag as an explanatory variable, in a case where the GMM-System model is employed. The main results find that lagged hate crime rate has a positive and statistically significant effect on the current hate crime rate. Thus, due to this positive relationship, it is important to add lagged hate crime in the current model. In this situation, GMM-System is an appropriate model since it was developed to eliminate the possible bias due to the inclusion of a lagged dependent variable.

The GMM-System estimator has a system of equations, in which one of them is expressed in a level form with first differences as instruments; in the other equation, it is expressed in a first-differences form, and the instruments are in levels. We use the two-step system GMM estimator since it is more efficient than the one-step estimate (WINDMEIJER, 2005). To test the validity of the instruments used in the model and, thus, the consistency of the GMM estimators, two specification tests are used. The first one is the Hansen test of overidentifying restrictions, in which the null hypothesis is the overall validity of the instruments. By using the J statistic of Hansen (1982), failing to reject the null hypothesis gives support to the model. The other specification test investigates if there is a second-order serial correlation of the differenced residuals. Failure to reject the hypothesis of no second-order serial correlation supports the model.

4. Results

4.1 Main Results

Table 2 reports the main results of estimations using GMM-System and, for comparison, a fixed-effects model, which is broadly used in hate crimes literature. In both models, the dependent variable is the hate crime rate by year and state, expressed in a natural logarithm. The results in columns (1) and (2) are obtained from the fixed effects model, in which control variables are used in the latter. Robust standard errors from this model are clustered by state. Columns (3) and (4) report the results of estimations using the GMM-System method, which considers the effect of lagged hate crimes on current rates. The results are once again from estimations without and with control variables.

By analyzing the results for the fixed effects model in column (2), we can see that there is a negative and statistically significant coefficient (-0.174) for *pres_dem*, which means that a Democratic president is correlated with 15.97% ($e^{-0.174}$ - 1) fewer hate crimes when compared to a period in which a Republican is in the presidency. A negative coefficient for this variable is also found in the OLS model. This result shows the importance of political parties in the presidency in terms of their influence on crimes, as Loureiro et al. (2018) show in terms of homicides in Brazil. There are some possible ways in which different political parties have different impacts on hate crimes. First, Democrats and Republicans represent different views on social issues (Moskowitz et al., 2019) and have different levels of identification according to the groups of voters: Republicans have an advantage in terms of electorate identification among white, men, rural communities, and religious population, while Democrats have an advantage among black, woman, Northern populations, and people with no religious affiliation (Pew Research Center, 2020). Those differences might reflect a different focus on public policies preventing hate crimes. As Democrats are more liberal on cultural issues and, at the same time, have higher levels of identification within the African American population (the main victims of hate crimes), they might as well make more efforts – or, at least, act more efficiently – addressing hate crimes. Second, by electing a given political party, it might change social norms and reveal preferences of a share of the electorate (Bursztyn et al., 2020), giving more confidence to more extreme partisans to endorse violence against their opponents (EDWARDS & RUSHIN, 2018). This might partially explain, for example, the recent rise in the number of right-wing terrorism attacks in the United States compared to the left-wing ones (Jones et al., 2020).

A positive coefficient for Democratic state governor (*gov_dem)* is found in the fixed effect model (column 2). This coefficient is significant at the 5 percent level. Contrary to the presidency, here a governor from the Democratic party is found to be correlated to 9.20% ($e^{0.088}$ – 1) more hate crimes when compared to a Republican. This shows how the dynamics in state politics might be different from the politics at a federal level in terms of influence on hate crimes. Party identification, social issues and party influence on public policy issues might be different between the state and federal levels.

Another positive coefficient is the one for elections, which is statistically significant at the 10 percent level. This means that, compared to other years, presidential election years have 7.25% ($e^{0.070}$ – 1) more hate crimes. This result is consistent with the idea that this is a period of more political polarization and inflammatory rhetoric during political campaigns, in a way that might induce more hate crimes (Edwards & Rushin, 2018). As Kalmoe and Mason (2019, p. 3) point out, "inducing expectations of electoral victory in the next presidential election gives strong partisans more confidence to endorse violence against their partisan opponents."

By comparing the previous results to the ones in column (1), we can see that coefficients for Democratic governors and election years only have statistical significance when we control for other variables, showing the importance of the consideration of aspects such as economic and sociodemographic conditions. The results for these variables in column (2) show statistically significant results for the share of the state population that is black (*black_pct*), the share of state population covered by the hate crime statistics (*popshare*), and the rate of violent crimes (*violent_crime*). The first of these variables, *black_pct*, has a negative coefficient (-0.183), meaning that a higher share of African American people in the state population is correlated to fewer hate crimes. It is contrary to the minority threat theory, which predicts that the growth of a minority group represents a threat to the majority, inducing more hate crimes. On the other hand, it fits the idea shown by Disha *et al.* (2011) that a higher minority population decreases the chances of victimization of each member of the minority. As we use the measure of hate crimes as a proportion of the state population instead of the total number of hate crimes, the result is consistent with this idea.

The positive coefficient for *popshare* (0.445) was expected since a higher number of precincts reporting hate crimes will shed light on the real number of hate crimes. In opposition, a lower share of the population covered by these statistics will have an artificially lower number of hate crimes due to hidden crimes that are unreported. Another positive and statistically significant coefficient is found for the rate of violent crimes (1.036). This is consistent with the literature, as in Disha et al. (2011), who show how hate crimes partially reflect general patterns of criminal activities. It helps to explain why there is a higher rate of hate crimes during the Clinton administration and a decrease afterward due to a general trend in violent crimes in the period.

Subsequently, results for the GMM-System model are shown in columns (3) and (4), in which such a model tests the idea that the hate crimes rate in the previous year affects the current rate. It also helps us to test the sensitivity of the results found by the fixed effects model in column (2). By considering the results in column (4), we can see that the *pres_dem* coefficient is also negative (-0.245) and statistically significant. This is a fact for both specifications using control variables (columns 2 and 4), representing a robust result. It confirms the fact that a Democratic president is correlated to fewer hate crimes ($e^{-0.245} - 1 = -21.73\%$, in this case) compared to a Republican. A positive coefficient for *gov_dem* also remains (0.062), although statistically significant only at the 10 percent level this time. Here, Democratic governors are correlated with 6.40% ($e^{0.062} - 1$) more hate crimes if compared to Republicans. On the other hand, the *elections* dummy does not have a statistically significant coefficient, which shows that the previous positive result in the fixed effects model did not take into consideration the effect of lagged hate crimes. Thus, there is no robust evidence that presidential election years are correlated to more hate crimes, at least during the analysed period.

Table 2. Political factors, economic factors, sociodemographic factors, and hate crimes

	Fixed effects	Fixed effects	GMM-System	GMM-System
	(1)	(2)	(3)	(4)
pres_dem	-0.170***	-0.174***	0.513***	-0.245**
	(0.032)	(0.034)	(0.107)	(0.109)
gov_dem	0.053	0.088**	0.049***	0.062*
	(0.039)	(0.036)	(0.014)	(0.033)
Elections	0.047	0.070*	0.556***	-7.776
	(0.039)	(0.037)	(0.093)	(6.394)
ln(unemployment)		0.042		0.303**
		(0.059)		(0.127)
ln(gdp_pc)		-0.292		0.807*
		(0.184)		(0.440)
ln(police_spending)		-0.055		0.100
		(0.068)		(0.128)
ln(black_pct)		-0.183***		-0.083
		(0.066)		(0.058)
ln(young_pct)		-0.236		-0.413
		(0.212)		(0.472)

ln(popshare)		0.338***		0.445***
		(0.049)		(0.069)
ln(violent_crime)		1.036***		-0.061
		(0.090)		(0.087)
ln(hate_crime)$_{t-1}$			0.830***	0.436***
			(0.031)	(0.041)
AR(2)			0.099	0.099
Hansen test			0.212	0.411
R^2	-0.017	0.146		
N	1,074	1,045	995	995

Note. Significant at * 10%, ** 5%, *** 1% level. Standard errors are in parentheses. Variables are instrumented by lagged own variables. GMM-System procedures are used using the xtabond2 command in Stata by Roodman (2009).

Subsequently, results for the GMM-System model are shown in columns (3) and (4), in which such a model tests the idea that the hate crimes rate in the previous year affects the current rate. It also helps us to test the sensitivity of the results found by the fixed effects model in column (2). By considering the results in column (4), we can see that the *pres_dem* coefficient is also negative (-0.245) and statistically significant. This is a fact for both specifications using control variables (columns 2 and 4), representing a robust result. It confirms the fact that a Democratic president is correlated to fewer hate crimes ($e^{-0.245} - 1 = -21.73\%$, in this case) compared to a Republican. A positive coefficient for *gov_dem* also remains (0.062), although statistically significant only at the 10 percent level this time. Here, Democratic governors are correlated with 6.40% ($e^{0.062} - 1$) more hate crimes if compared to Republicans. On the other hand, the *elections* dummy does not have a statistically significant coefficient, which shows that the previous positive result in the fixed effects model did not take into consideration the effect of lagged hate crimes. Thus, there is no robust evidence that presidential election years are correlated to more hate crimes, at least during the analysed period.

Another important result captured by the GMM-System model is that lagged hate crime rate indeed affects the current hate crime rate, in a coefficient (0.436) that is statistically significant at the 1 percent level. It means that hate crimes in the United States have an inertial behaviour. This is consistent with what is found by Mulholland (2013) considering hate crimes. The empirical literature on other types of crime finds similar behaviour when using a dynamic model. See Fajnzylber et al. (2002), Choe (2008), and Loureiro et al. (2018), for example. Thus, it is necessary to reinforce the importance of using the GMM-System model to properly identify the factors influencing hate crimes. According to Fajnzylberg et al. (2002), there are two channels in which lagged crime influences actual crime. First, there is a decrease of costs involving crime activities, since criminals might learn by doing, reducing the moral loss associated with the crimes and increasing interactions between criminals. Second, as the police and the judicial system fail to respond to a rise in crimes, this might reduce the perceived probabilities of apprehension.

Further results by the GMM-System model in column (4) present similarities and differences from the previous model in column (2). Reinforcing its importance on the model, *popshare* has once more a positive and highly significant result. Considering the proportion of state population that is covered by these statistics is, therefore, a crucial step into addressing imperfect reports. Some other control variables, however, present different results. The share of the state population that is black (*black_pct*), for example, loses its statistical significance, in a way that we might not consider any effect of the share of the African American population in hate crimes. After controlling for lagged hate crimes, the effect of *black_pct* might be already captured, for example, by state fixed effects, resulting in a coefficient that is not significant in statistical terms.

The GMM-System results also have two control variables with significant results – in opposition to the fixed effects results: *unemployment* and *gdp_pc*, which represent the unemployment rate and the real Gross Domestic Product (GDP) per capita. Thus, by considering the dynamic effects of hate crimes, we can see that economic factors influence hate crime rates. According to the results shown in column (4), a higher unemployment rate is correlated with more hate crimes. Consistent with what is found in hate crime literature (Ryan & Leeson, 2011; Entorf & Lange, 2019; Gale et al., 2002 Medoff, 1999), the unemployment might induce more time to criminal behaviour, increasing hate crimes, such as shown by the economic theories. Additionally, unemployment might be seen as a perceived threat of outer groups, such as the minority threat theory, inducing hate crimes. The other economic variable, *gdp_pc*, has also a positive coefficient, meaning that higher per capita income is correlated with higher hate crimes. Literature has ambiguous results in terms of connections between income and hate crime rates. These results might represent that, *ceteris paribus*, hate crimes occur more in richer states. In terms of validity of the model, specifically in the complete GMM-System presented in column (4), the Hansen test shows an overall validity of the instruments. The Arellano-Bond (AR) autocorrelation test shows no second-order serial correlation.

4.2 Robustness

We conduct a series of sensitivity analyses to ensure that the main results about political parties and hate crimes are robust. The robustness checks are conducted using the main GMM-System model due to its use of lagged hate crime rates, an important variable to be considered (as shown by the main results). Three different specifications are used, and their results are discussed.

A possible problem that might deteriorate the results is the presence of outliers. Although the sample presents an average rate of 24.61 hate crimes per million, some observations report rates over 100. As the box plot in Figure 2 shows, there is a presence of outliers above the region that is 1.5 times the interquartile range above the upper quartile. Therefore, we address this issue in a similar approach conducted by Lin (2007) by deleting all observations above the 95th percentile. Results are shown in column (1) of Table 3. It is possible to observe that the main results concerning hate crimes and political determinants remain.

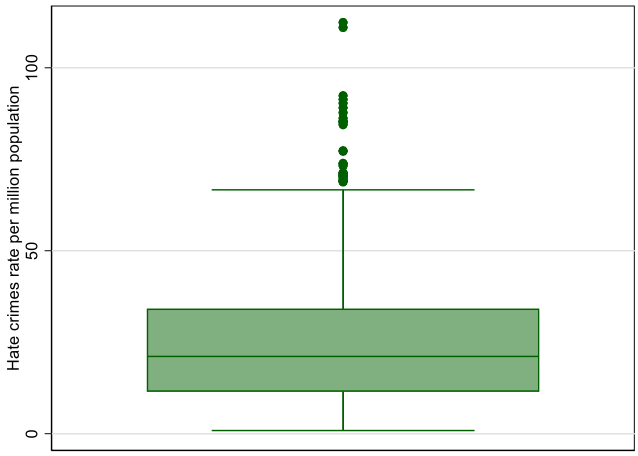

Figure 2. Box plot of hate crime rates

Source: Prepared by the authors.

Another possible channel that might influence hate crimes is the internet, which can offer a greater opportunity to engage in hate crime groups and more access to hate speech (Müller & Schwarz, 2018; Finkelstein et al., 2020). On the other hand, it may offer greater access to information and integration between groups. we use the share of the state population that has access to the internet (Tolbert & Mossberg, 2015) to check if it has any effect on hate crimes and if it impacts the main results. Results are shown in column (2) of Table 3. The results for the three political variables remain like the main results previously found. However, there is not a statistically significant result for the internet access variable, meaning that this model was not able to find any significant relationship between internet access and hate crimes. This effect might have been captured by the state fixed effects or other variables such as the economic determinants.

Table 3. Robustness tests

	(1)	(2)	(3)
pres_dem	-0.235**	-0.969**	-0.070
	(0.104)	(0.415)	(0.485)
gov_dem	0.083**	0.074*	-0.621*
	(0.041)	(0.040)	(0.327)
elections	0.135	0.451	0.072
	(0.137)	(12.575)	(0.260)
ln(hate_crime)$_{t-1}$	0.357***	0.332***	0.411***
	(0.047)	(0.067)	(0.052)
ln(internet_access)		1.590	
		(1.094)	

pres_south			-1.077**
			(0.437)
gov_south			2.500**
			(1.152)
elections_south			-0.192
			(0.441)
south			1.256
			(1.549)
Control variables	Yes	Yes	Yes
AR(2)	0.144	0.100	0.853
Hansen test	0.285	0.586	0.400
N	949	995	995

Note. Significant at * 10%, ** 5%, *** 1% level. Standard errors are in parentheses. Variables are instrumented by lagged own variables. GMM-System procedures are used using the xtabond2 command in Stata by Roodman (2009).

Another concern related to the results is that they might have a heterogeneous result according to the region. More specifically, the South might have some characteristics that differ from the other regions since, during its origins, the Democratic party used to defend the interest of Southern slaveholders. In fact, until the mid-20th Century, there were Southern Democrats opposed to civil rights. As these historical facts might have a different influence on how the political determinants impact hate crimes, the Southern Region needs to be treated differently. A similar approach is found in hate crime literature, such as Gale et al. (2002). Here, we add a South dummy (that equals one when there is a Southern state and zero otherwise) and its interactions with the three political variables: *south* x *pres_dem* (*pres_south*), *south* x *gov_dem* (*gov_south*), and *elections* x *south* (*elections_south*).

Results are shown in column (3) of Table 3, corroborating the idea that there are different effects in Southern and non-Southern states. The interaction between *pres_dem* and *south* has a negative and statistically significant result, while *pres_dem* does not have a significant result. According to this result, the negative effect of a Democratic president (compared to a Republican) is captured by the Southern states. This might show how different political discourses and policies can effectively affect hate crimes in the South. When looking at the state government results, there is a different pattern from the main results. While *gov_dem* has a positive coefficient in column (6) of Table 2 (0.062), the coefficient here in Table 3, column (3) shows a different result: there is a negative and significant relationship (-0.621) between a Democratic governor and hate crimes (compared to Republicans). This means that, in non-Southern states, a Democratic governor is correlated with 46,26% ($e^{-0.621} - 1 = 0.4626$) fewer hate crimes if compared to a Republican governor. The positive relationship previously found was due to the Southern states: *gov_south* has a positive and significant coefficient (2.500). It represents a net positive effect of Democratic governors in the Southern region. Such results might show how the historical conditions in the Southern region might still prevail. The interests and ideology of the Democratic party since its foundation until the mid-20th Century might have affected institutional and cultural determinants in the region. Hence, the results discussed here show how there are differences between the South and other regions in terms of political parties and hate crimes. Specifically concerning the presidential elections, however, there are still no significant effects.

5. Conclusion

The present work investigated the relationship between political parties in power and hate crimes in the United States. Additionally, it tries to find if there is any relationship between these crimes and presidential election years. We find robust evidence that lagged hate crimes have a positive and significant effect on actual hate crime rates. In addition, results show robust evidence that Democratic presidents are correlated with fewer hate crimes if compared with Republicans. This may occur due to different public policies conducted by each party, as they have different views on social issues (Moskowitz et al., 2019). It is also possible that this is an effect of inflammatory rhetoric (Edwards & Rushin, 2018), change of social norms (Burzstyn et al., 2020), and more (or less) identification with given groups (Pew Research Center, 2020).

We also find that Democratic governors are correlated with more hate crimes, showing how parties might differ in terms of public policies if comparing the state and federal levels. However, further tests controlling for regional differences show that this result only remains for Southern states, as Democratic governors in non-Southern states have a negative relationship with hate crime rates. This not only shows how regional effects might differ but also demonstrates how the historical conditions in the South might still affect present issues such as hate crimes. Additional results found no statistically significant results concerning the effect of presidential election years, even when considering regional aspects.

As this work investigates the effect of different political parties on Executive and hate crimes, further developments can be made. An investigation on the effects of Legislative control can be made since it also influences public policies. The relationship between political polarization and hate crimes can also be investigated as this is a growing concern in the United States (Canen et al., 2020). Additionally, further developments for the present work can be made aggregating hate crime data to the county level, as it increases the number of observations and improves models.

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