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POLITICAL PARTIES AND HATE CRIMES: EMPIRICAL EVIDENCE FROM THE UNITED STATES

Matheus Augusto Santana Souza

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Dissertação apresentada ao Departamento de Economia da Universidade de Brasília (UnB) como requisito parcial à obtenção do título de Mestre em Economia.

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_____
Paulo Roberto Amorim Loureiro
Orientador

_____
Geovana Lorena Bertussi
Membro Interno

_____
Tito Belchior Silva Moreira
Membro Externo

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RESUMO

Este trabalho tem como objetivo investigar a relação entre partidos políticos e crimes de ódio nos Estados Unidos. Adicionalmente, analisa-se um possível impacto dos anos de eleição presidencial nas taxas de crime de ódio. Para atingir estes objetivos, são usados os modelos de efeito fixo e GMM-System. O último é usado como modelo principal devido ao uso de taxas defasadas de crimes de ódio, que a literatura aponta como uma importante variável a ser considerada. Um modelo de dados em painel com 47 estados de 1997 a 2019 é construído, sendo usados dados de crimes de ódio do FBI, bem como variáveis políticas, econômicas e sociodemográficas. Os resultados mostram que um presidente democrata é correlacionado com menos crimes de ódio se comparado a um republicano. Em adição, mostra-se que governadores democratas têm uma correlação positiva com crimes de ódio, mas exercícios adicionais mostram que isso é válido apenas para estados do Sul. Em estados fora do Sul, governadores democratas são negativamente correlacionados com crimes de ódio. Isto mostra como condições históricas no Sul podem continuar afetando as políticas públicas atuais, bem como as taxas de crime de ódio. Não são encontrados resultados estatisticamente significantes com respeito ao efeito dos anos de eleição presidencial.

Palavras-chave: crimes de ódio, partidos políticos, causas de crime, GMM-System.

ABSTRACT

This work aims to investigate the relationship between political parties and hate crimes in the United States. Additionally, it analyses if presidential election years have any impact on hate crime rates. To achieve these objectives, the fixed effects and the GMM-System models are used. The latter is used as the main model due to the use of lagged hate crime rates, which is found in the literature to be an important variable to consider. A panel data with 47 states from 1997 to 2019 is constructed using hate crime data from the FBI as well as political, economic, and sociodemographic variables. Results show that a Democratic president is correlated with fewer hate crimes if compared with a Republican. In addition, it is found 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. This shows how historical conditions in the South might continue to affect current policies and hate crime rates. No statistically significant results are found regarding the effect of presidential election years.

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

SUMÁRIO

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 and 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 and 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 behavior, 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 and 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 and WOOD, 1999; GILES and 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 *et al.*, 2004; MÜLLER and 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) show 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 this party. 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 analyzing 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 W. Bush (26.89) and Donald Trump's (22.9) Republican mandates. Even though Clinton's second mandate (which was analyzed 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 and RUSHIN, 2018).

Thus, I use an empirical approach to analyze 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, I verify if there is a positive relationship between hate crimes and presidential election years. I 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 analyzed the importance of access to hate speech (MÜLLER and SCHWARZ, 2020), support to far-right politicians (REES *et al.*, 2019), and the election of a given president[1] (EDWARDS and RUSHIN, 2018) in terms of raising hate crimes. Considering the polarization of American political parties in terms of social issues (MOSKOWITZ *et al.*, 2019), I contribute to the hate crime and political economy literature by empirically analyzing a possible direct relationship between hate crimes and political parties in power. To achieve these objectives, I first review the hate crime literature, describing its main

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[1] Edwards and Rushin (2018), for example, see the case of electing Donald Trump to the presidency in the United States and its relationship with hate crime rates.

theories and evidence. I also present data and methodology to be applied and, subsequently, I discuss the results and robustness tests.

It is important to stress that the initial objective of this dissertation was to analyze hate crime determinants in Brazil. However, the lack of available data has made it difficult to achieve this objective, since it would be hard to construct reliable panel data for hate crimes in the country. Some initiatives contribute to better understanding the Brazilian scenario, such as the non-profit organization Words Heal the World, which has produced the Hate Map of Brazil for 2018 and 2019. But, as the reports emphasize, there are many differences in the reports of each state, as well as many under-reported hate crimes (WORDS HEAL THE WORLD, 2021). In any case, considering that political parties in Brazil might affect policies and crime rates differently (LOUREIRO *et al.*, 2018) and that the country has a growing political polarization (CHAIA and BRUGNAGO, 2014; VALENTE *et al.*, 2020), the results found in this work might shed light on the Brazilian case. A better understanding of the determinants of hate crime is an important factor to address this question more effectively.

The dissertation is organized as follows. Beyond this Introduction in Chapter 1, I 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, I discuss the results and further perform robustness tests. Concluding remarks are presented in Chapter 5.

2. LITERATURE REVIEW

This chapter aims to present which are the main theories and empirical evidence related to hate crimes. The review allows a better comprehension regarding this type of crime, as well as its determinants. I present theories from Economics, Social Psychology, and Criminology, besides exposing papers that aim to determine – or not – the empirical validation of indicated determinants. After this, I address theories and respective empirical evidence on the influence of political factors in hate crimes. Factors such as polarization, ideology, and the influence of politicians are presented, demonstrating their relationship to prejudice and violence against certain groups. I also present a historical context regarding the relationship between political parties and

race due to the relative importance of hate offenses motivated by a race, ethnicity, and/or ancestry bias in the American context.

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 behavior modeled 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. The model is applied to the racial conflicts in the United States, in which it assumes that the white majority prefers a higher relative wage compared to the non-white minority. Reducing this relative difference can encourage the envious members in the majority to reduce the other group's utility, increasing hate crimes committed by the white majority. On the other hand, raising the wage gap can induce the non-white minority members to become more hostile, leading them to commit more hate crimes.

In another economic model, Medoff (1999) uses the economic approach of rational choices by Becker (1965), beyond an analysis guided only by monetary and market issues, to explain hateful behavior. The model assumes that an individual's utility depends on the consumption of antisocial hateful behavior (defined as H) as well as an aggregate good (Z) that combines all other products. It assumes the hateful behavior to be time-intensive and the individual must allocate its time among working, producing H, and producing Z. According to the author, an increase in market wage would drive a decrease in hateful activities. Moreover, an individual has a higher propensity to hateful activities while young. Consistent with other crime-related economic theories, greater law enforcement is related to fewer hate crime activities.

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 and MCDEVITT, 1993). Accordingly, Dharmapala and Garoupa (2004) extend the standard crime models assuming identical harm to victims of hate crimes and unbiased crimes. However, the authors endogenously derive social harms, resulting in disparities due to biased selection of victims. Their central idea is that targeted groups avoid certain activities with the dominant group to reduce the probability of victimization. Thus, there is a renounce to possibly profitable activities, generating a social loss. As a result, a crime disproportionately targeting a certain group causes greater harm than crimes in which victims are randomly chosen.

Gan *et al.* (2011) find a similar result by creating a model of optimal hate crime legislation. The model assumes differences between hate crimes and other crimes. First, it assumes the utility of those who commit hate crimes to have a lower weight in the government's objective function, if compared to other criminals. Besides, it assumes negative externalities caused by hate crimes, like psychological harm to members of a targeted group, as well as a greater effort to avoid being a victim. It also assumes that it is harder to avoid being a victim of hate crimes compared to other crimes: besides the difficulty to hide being identified as a member of a targeted group, a lower number of potential victims raises one's possibility to become a hate crime victim. All these factors assumed, the authors conclude that a different level of effort must be considered to address hate crimes.

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 try to empirically find evidence to the introduced model. Using FBI hate crimes data, they construct a panel data model using several socioeconomic and demographic variables. As a result, the model points out 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. It is consistent with the presented theory and emphasizes the differences between hate crimes and other crimes.

Medoff (1999) also tests empirically his theory using FBI hate crimes data. He uses socioeconomic, demographic, and religious variables to find possible determinants of hate crimes. The author finds results that are consistent with the theory, such as the fact 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. It is worth mentioning the fragility of results due to the use of the ordinary least squares model, which can generate inconsistent generators in such analysis.

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. Using a negative binomial model to deal with excessive variability, the authors use demographic and socioeconomic variables. 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. Defining as exogenous the distribution of asylum seekers throughout the country, the abrupt shift in the number of immigrants in different regions is used as a quasi-experiment to analyze hate crimes determinants. 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. Initially, there is evidence that economically deprived regions are prone to hate crimes. However, by controlling for differences between East and West Germany, economic factors no longer explain hate crimes.

Fryer Jr. and Levitt (2012) analyze the determinants of Ku Klux Klan membership during the 1920s, as well as its political and social influence. Initially, they present a theoretical model in an extensive form of a game to represent Klan membership. This decision is found to be influenced by the costs and benefits of remaining in the Ku Klux Klan, the group's reputation, and the type of player in the model. The authors also construct a database of members of the Klan in the 1920s, during its peak of popularity. A simple logistic specification model shows that there was a higher probability of membership for higher native-born rates and literacy rates and,

in some cities, the rate of professionals (such as lawyers, doctors, and engineers). They find no relationship between membership and age, the propensity to be married or to be the head of household. Further data present little evidence on the Klan influencing vote totals or black and foreign-born mobility.

2.2 SOCIAL PSYCHOLOGY AND CRIMINOLOGY THEORIES

Generally, the economic approach to hate crimes uses a rational aspect of criminal behavior, 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) address 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. Beyond the study by Entorf and Lange (2019), discussed in the last section, there are several shreds of evidence on these theories, such as the paper by Jacobs and Wood (1999). They 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. Therefore, the paper brings favorable evidence to the idea that growing minorities can represent a threat to the majority group. In this case, economic rivalries between groups can result in more conflicts.

Another racial issue is addressed by Giles and Buckner (1993) by observing a U.S. Senate race in the state of Louisiana. The Republican candidate, David Duke, had a political position guided by extreme social conservatism, where he was previously a member of groups such as the Ku Klux Klan (GILES and BUCKNER, 1993). Thereby, the authors seek to understand the determinants of white support for Duke. As a result, they find that a higher percentage of black people in a region results in a higher tendency to white mobilization for Duke. They observe that this is evidence that the threat factor continued to operate. A higher proportion of the black population was a threat to white political hegemony, resulting in a higher hostility throughout voting for a racist candidate.

Disha *et al.* (2011) investigate 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. Therefore, they show that terrorist attacks can incite more hate crimes as retaliation since there was a higher perception of threat by certain minorities.

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 behavior. 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. They find these results through two experiments designed to reveal preferences and to sanction xenophobic behavior. They also indicate that the pointed mechanisms may explain factors such as the vote for Brexit and the increase in negative feelings toward immigrants and minorities in developed countries.

Elections and political discourses can also influence hate crime itself. Edwards and Rushin (2018), for example, 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 behavioral forms of political extremism. They show that both factors have similar psychological and social structures, signaling that support to far-right politicians might be an additional indicator of areas with high extremism risk. By separately analyzing West and East Germany municipalities, the authors find that electoral support to the far right is positively correlated with the unemployment rate and negatively correlated with the proportion of immigrants. In turn, right-wing hate crimes are positively correlated with the unemployment rate, but there is only a significant result to immigrant rate in East municipalities, in a positive correlation.

Beyond support to far-right politicians, extreme ideologies discourses can also affect violence against certain groups, which also includes far-left ideologies. Far-left groups and intellectuals 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. It is necessary to emphasize that anti-Jewish bias is a significant problem in the United States. Hate crime statistics show that, among the victims of anti-religious hate crimes in 2019, 60.2% of them were victims of crimes committed by offenders' anti-Jewish bias (FBI, 2019).

To demonstrate how the channel between extreme ideologies discourses and hate crimes works, Glaeser (2005) develops a model in which politicians can supply stories that generate hate since their policies complement this hatred (for example, a candidate adverse to redistribution spreading hate against a poor minority[2]). Hate speeches against a targeted group, according to the author, are specially made through stories of crimes committed by this group. A greater effect can be obtained with repetition, and not necessarily with facts. On the demand side for hate speeches, greater effects are obtained on voters with less private incentives to search for the veracity of facts due to its higher costs.

Using data from newspapers and police reports in Germany, Koopmans, and Olzak (2004) analyze this channel for the German case. They find evidence that the higher the visibility, resonance, and legitimacy of right-wing violence, the higher is the probability of hate crimes. In a more recent study, Müller and Schwarz (2020) address the link between discourse visibility and hate crimes by using data analysis in social media. They show that, during periods with a higher influx of immigrants, areas more exposed to a Facebook page of a far-right party (with discourses against immigrants and hate speech) tend to have more hate crimes.

The literature, thus, indicates that extreme ideologies and grievances toward groups, especially through their visibility and legitimacy, can influence the increase in hate crimes. Increased animosity between groups is an important factor to be observed in this way, 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

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[2] The opposite might also happen when a candidate who is favorable to redistribution spreads hate against a rich out-group.

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 analyzing 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. Considering that, during the period that the Workers' Party was in presidency, there was a reduction in poverty and inequality, it might be seen through the minority threat theory as a possible threat to the social and economic status of the elites, possibly resulting in more discrimination, group confronts, and crimes.

Presidents' actions and words might affect how the population behaves during certain circumstances. For instance, Ajzenman *et al.* (2020) analyze how Brazil's president influenced the behavior of the population during the COVID-19 pandemic in 2020. The paper shows that, by underestimating the risks during the pandemic and advising against social isolation, the president's words resulted in less social isolation during the subsequent days, especially in localities where the president had higher political support. Figueira and Louzada (2021) corroborate this idea. The authors, thus, stress the importance of a public leader such as the head of state in the change of behavioral changes among the population. Similarly, by adjusting it to the case of hate crimes, words and actions of a president might influence a sense of union – or hate – among the population and its different groups, reflecting on the rate of hate crimes.

Evidence shows the influence of politicians on the population behavior, whether in the change of social norms (BURSZTYN *et al.*, 2020) or violent behavior through hate crimes (KOOPMANS *et al.*, 2004; EDWARDS & RUSHIN, 2018; MÜLLER & SCHWARZ, 2020). Also because political parties have different views on social issues (MOSKOWITZ *et al.*, 2019) and even have a different impact on homicide rates (LOUREIRO *et al.*, 2018), it is important to address the question of whether political parties affect hate crime rates differently. Thus, this study aims to empirically analyze 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.

2.3.1 Politics and Race throughout American History

An important topic when addressing hate crimes in the U.S. is the racial issue and its relationship with political parties. FBI data shows that most hate offenses reported in 2019 were motivated by a race, ethnicity, and/or ancestry bias (57.6%), from which 48.4% of them had an anti-Black or African-American bias and 15.8%, anti-White bias. On the other hand, 52.5% of the known offenders during that year were White and 23.9% of them, Black or African-American (FBI, 2019).

While racial tensions continue to be present in American society, it is also a fact that party identification is still linked to race. According to research by the Pew Research Center (2020), while 53% of the registered white voters identify as a Republican (or lean Republican), 83% of the Black registered voters identify themselves as Democrats (or lean Democrats). Considering that social issues are an important factor in the recent growth in political polarization (MOSKOWITZ *et al.*, 2019), understanding the roots of its connections to racial issues is a necessary condition to this work.

Although, as previously shown, the African-American population is mostly identified to the Democratic party in the present day, this was not always the case. The origins of the two main political parties in the U.S. reveal a different pattern. In a period when slavery divided Northern and Southern Americans, the Democratic Party was a defender of Southern slaveholders' interests. The Republican Party, in its turn, represented especially a Northern and antislavery view. Slavery became a dominant issue by the time of the Republican party's foundation when such tensions contributed to the subsequent Civil War (CRITCHLOW, 2015).

The following period was marked by the emancipation of slavery, especially through the 13th Amendment, which was a political effort of Lincoln and Republicans in Congress (as well as the effort of many citizens and groups). The 13th Amendment gave a legal foundation to emancipation, in a process that continued to occur. The emancipation of slavery was not a synonym of racial equality since political, economic, and social aspects continued to be a source of inequality between white and African-

American populations. This was a major problem during the Reconstruction that followed the Civil War. As Mickey (2015, p. 37) points out: "After Emancipation, the overarching political-economic question in the region remained whether, and how, large landowners would develop a reliable supply of labor. They soon chose to pursue their goals through state Democratic parties".

This racial inequality was reinforced by the introduction of the Jim Crow laws. This set of state and local laws mandated racial segregation in Southern states, disenfranchising the African-American population and separating people according to race in public facilities, such as schools, hospitals, and public transportation (FREMON, 2000; SCHICKLER, 2016). This process was partly due to a failure by the northern Republicans to provide military, economic, and political investments to properly reconstruct the South (SCHICKLER, 2016).

Disenfranchisement was partially a reaction from the Southern Democrats to the support of the African-American population to Republicans, as well as to the election of black southern candidates. By imposing literacy tests, poll taxes, and other instruments, the black-belt whites maintained their status. Otherwise, a competition between the two parties in the South would destroy the Democrats' unity in the national scene and, consequently, their authority (KEY, 1949). On the other hand, the black population continued to have a greater identification with the Republican Party during many years ahead (SCHICKLER, 2016).

This identification started to change during the 20th Century, in a process of party realignment. In fact, until the New Deal, most white southerners were identified as Democrats. However, it started to change with an approximation of certain Democratic politics, including the president Harry Truman in 1948, with civil rights policies. The rise of a movement for civil rights united, on the one hand, liberal Republicans and Democrats that voted for civil rights; on the other hand, Southern Democrats and conservative Northern Republicans were opposed to it. This movement culminated in the Civil Rights Act of 1964 and the Voting Rights Act of 1965, which outlawed discrimination and racial segregation, as well as increased the participation of the black population in the democratic process (LEVITSKY and ZIBLATT, 2018).

The Civil Rights Act had the support of Democrat president Lyndon Johnson, while Barry Goldwater, the Republican candidate, was opposed to it. Additionally, the use of the Southern Strategy by Nixon and the Republican Party to gain Southern support from the white population, as well as Ronald Reagan's politics and discourses

viewed by some as an "aggressive race-baiting" (HANEY-LÓPEZ, 2015, p. 56), contributed to the party realignment and the shift of party identification (LEVITSKY and ZIBLATT, 2018).

This new party identification remains until nowadays, as cited before, with the majority of the African-American population identifying as Democrat or lean Democrat, while the white population, especially the Southern one, identifies more with the Republican Party. By considering that racial bias is the main motivation behind hate crimes in the United States today, we can see that this is a historical problem (as briefly discussed in this subsection) that persists and, at the same time, has its connections with politics and political parties. By considering how, as literature shows, hate crimes might be connected to politics and political discourses, it is important to see if there is a correlation between political parties in power and hate crimes, that has a racial bias as the main motivation today, but might occur due to other motivations as well.

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. I 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) show 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 analyzed data), there is an increase of hate crimes compared to the previous year. Thus, I also analyze 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 and RUSHIN, 2018; KALMOE and MASON, 2019).

To investigate a possible relationship between political parties in the presidency and hate crimes, I 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. I 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, I 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, I 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.
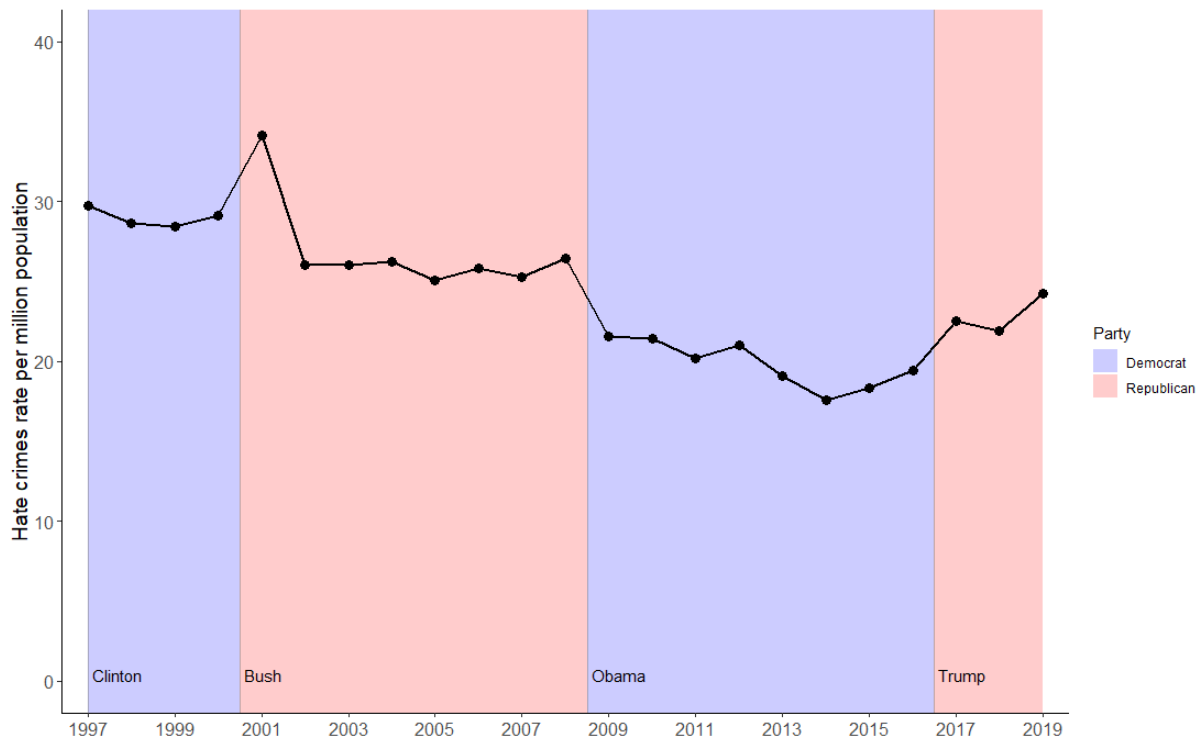
Source: FBI (2019), prepared by the author.

I 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[3] (*gdp_pc*), 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). I 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

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[3] In 2019 dollars.

differences in citizens' protection against crime." In addition, I use the violent crime rate (*violent_crime*), which includes homicide, rape, robbery, aggravated assault, property crime, burglary, larceny, and motor vehicle theft. I use this following Disha *et al.* (2011), which points out that hate crimes might reflect general patterns of criminal activities. Finally, I also use the percentage of the state population that is covered by the UCR's hate crimes statistics each year. Thus, I address the problems that arise due to imperfect reports, accounting for changes in coverage share (RYAN and LEESON, 2011; EDWARDS and RUSHIN, 2018; GALE *et al.*, 2002).

I get data for these variables from the FBI's Uniform Crime Reporting Statistics, the U.S. Bureau of Labor Statistics, the Bureau of Economic Analysis, and the United States Census Bureau. I 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 author.

3.2 EMPIRICAL APPROACH

To investigate possible correlations to hate crime, I first construct an empirical model estimating the following two-way fixed effects model with standard errors clustered by state:

$$hate\_crime_{it} =$$
$$\alpha.e^{\gamma P_t + \delta E_t + \eta G_{i,t}}.Economic_{i,t}{}^{\beta_1}.\ Sociodemographic_{i,t}{}^{\beta_2}.Popshare_{i,t}{}^{\beta_3}.e^{\Phi_i + \zeta_t + \varepsilon_{i,t}}\quad for\ i = 1, ..., N;\ t\ =\ 1, ..., T \qquad (1)$$

Or in a logarithmic form to express coefficients in terms of elasticities:

$$ln(hate\_crime_{i,t})\ =\ \beta_0 + \gamma P_t +\ \delta E_t + \eta G_{i,t}\ +\ \beta_1 ln(Economic_{i,t}) +$$
$$\beta_2 ln(Sociodemographic_{i,t}) + \beta_3 ln(Popshare_{i,t}) + \Phi_i +\ \zeta_t +\ \varepsilon_{i,t}\ for\ i\ =\ 1, ..., N;\ t\ =$$
$$1, ..., T \qquad (2)$$

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. Φi and ζ$_t$ are, respectively, state and year fixed effects. State fixed effects control for time-invariant differences across states that might influence hate crimes, such as culture or institutions. Year fixed effects, on the other hand, control for aspects that are similar in every state, but change across time and might affect hate crimes as well. ε$_{i,t}$ is a random error term. The use of a fixed-effects model was chosen to follow most of the empirical literature on hate crime, such as Ryan and Leeson (2011), Entorf and Lange (2019), King *et al.* (2009), Gale *et al.* (2002), and Edwards and Rushin (2018).

To check whether lagged hate crime rates affect current hate crime rates, I further 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):

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

(3)

Beyond the previously cited variables, it also includes the lagged hate crimes rate (*hate_crime*$_{i,t}$) and $v_{i,t} = \mu_i \ + \ \epsilon_{i,t}$, a vector of error terms. The disturbance term, $v_{i,t}$, 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[4].

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. I 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.

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[4] Nickell (1981) shows the existence of bias in a dynamic panel data model by applying an Ordinary Least Squared Method and using individual fixed effects.

4. RESULTS

4.1 MAIN RESULTS

Table 2 reports the main results of estimations using the previously discussed methods in which the dependent variable is the hate crime rate by year and state, expressed in a natural logarithm. Columns (1) and (2) are the results of estimations using the Ordinary Least Squares method with no year and state fixed effects nor a lagged dependent variable. These results are used to be compared to the other models. The results in columns (3) and (4) 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. By comparing the fixed effects and OLS results, it is possible to perceive differences due to the control for state and year effects in the former model. Finally, columns (5) and (6) 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. It is important to highlight that a random-effects model was also estimated; however, according to the results of the Hausman test, the fixed effects model has superiority over the random effects model in the analyzed data.

By analyzing the results for the fixed effects model in column (4), 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 and Northern populations, as well as 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 and 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 4). This coefficient is significant at the 5 percent level. Contrary to the presidency, in which a Democrat in power has a negative influence on hate crimes, here a governor from this same 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 (HAIDER-MARKEL, 1998). 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 and 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 (3), 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 (4) 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. These authors present a brief review of the idea that "minority group members are at a lower risk of victimization in areas where they constitute a higher proportion of the population because dominant group members may fear the consequences of their acts" (DISHA *et al.*, 2011, p. 24). As I 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 (even considering the political party in the presidency) since this was a general trend in violent crimes in the period.

If we compare the fixed effects and OLS results (columns (4) and (2), respectively) it is noticeable that there are many different results, especially in terms of statistical significance. Police spending, for example, has a significant result in the OLS model, but not in the fixed effect model (and there is also the opposite in other variables). Results in column (2) do not take into consideration factors varying over time and across states that also affect the rate of hate crime. Thus, results using the fixed effects are more reliable since such factors are considered.

Table 2 - Hate crimes and political, economic, and sociodemographic factors (1997-2019)

ln(hate_crime)	OLS	OLS	Fixed effects	Fixed effects	GMM-System	GMM-System
	(1)	(2)	(3)	(4)	(5)	(6)
pres_dem	-0.162***	-0.107*	-0.170***	-0.174***	0.513***	-0.245**
	(0.045)	(0.062)	(0.032)	(0.034)	(0.107)	(0.109)
gov_dem	0.163*	0.123	0.053	0.088**	0.049***	0.062*
	(0.095)	(0.079)	(0.039)	(0.036)	(0.014)	(0.033)
elections	0.041	0.063**	0.047	0.070*	0.556***	-7.776
	(0.025)	(0.028)	(0.039)	(0.037)	(0.093)	(6.394)
ln(unemployment)		-0.019		0.042		0.303**
		(0.129)		(0.059)		(0.127)
ln(gdp_pc)		0.459		-0.292		0.807*
		(0.384)		(0.184)		(0.440)
ln(police_spending)		0.315*		-0.055		0.100
		(0.186)		(0.068)		(0.128)
ln(black_pct)		-0.151		-0.183***		-0.083
		(0.093)		(0.066)		(0.058)
ln(young_pct)		-0.282		-0.236		-0.413
		(0.559)		(0.212)		(0.472)
ln(popshare)		0.671***		0.338***		0.445***
		(0.115)		(0.049)		(0.069)
ln(violent_crime)		0.072		1.036***		-0.061
		(0.159)		(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	0.016	0.193	-0.017	0.146		
N	1,074	1,045	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 (5) and (6), 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 (4). By considering the results in column (6), we can see that the *pres_dem* coefficient is also negative (-0.245) and statistically significant. This is a fact for all the models in specifications using control variables (columns 2, 4, and 6), 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 analyzed 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 behavior. This is consistent with what is found by Mulholland (2013) considering hate crimes. The empirical literature on other types of crime finds similar behavior when using a dynamic model[5]. 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 (6) present similarities and differences from the previous model in column (4). 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.

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[5] See Fajnzylber *et al.* (2002), Choe (2008), and Loureiro *et al.* (2018), for example.

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 (6), a higher unemployment rate is correlated with more hate crimes. Consistent with what is found in hate crime literature (RYAN and LEESON, 2011; ENTORF and LANGE, 2019; GALE *et al.*, 2002 MEDOFF, 1999), the unemployment might induce more time to criminal behavior, 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. However, 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 (6), 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

I 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, I 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, that is, there is still a negative coefficient for the Democratic President and a positive coefficient for the Democratic Governor, both statistically significant. The presidential election dummy still presents a statistically insignificant coefficient.

Figure 2 - Box plot of hate crime rates
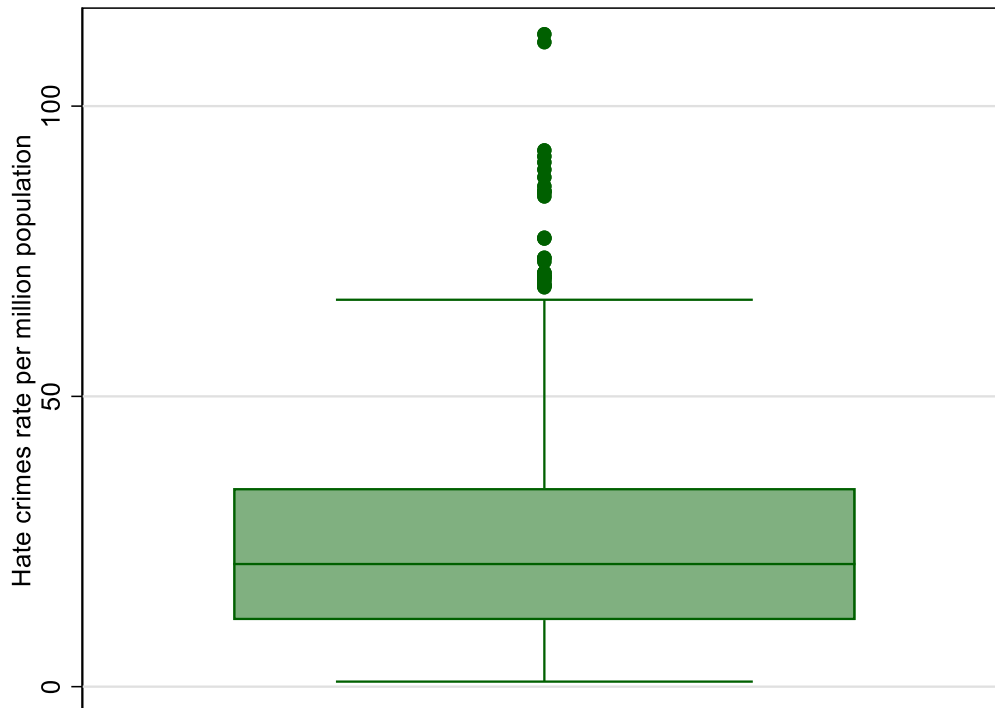
Another possible channel that might influence hate crimes is the internet, which can offer a greater opportunity to engage in hate crime groups and more access to hate speech (MÜLLER and SCHWARZ, 2018; FINKELSTEIN *et al.*, 2020). On the other hand, it may offer greater access to information and integration between groups. I use the share of the state population that has access to the internet (TOLBERT and 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 similar to 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 (1997-2019)

ln(hate_crime)	GMM-System (1)	GMM-System (2)	GMM-System (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(unemployment)	0.204	0.246	0.564
	(0.148)	(0.176)	(0.675)
ln(gdp_pc)	0.411	0.219	0.328
	(0.651)	(0.889)	(1.536)
ln(police_spending)	0.158	0.147	0.137
	(0.178)	(0.163)	(0.283)
ln(black_pct)	-0.080	-0.032	-0.169
	(0.063)	(0.088)	(0.211)
ln(young_pct)	-0.106	-0.242	1.043
	(0.654)	(0.654)	(1.074)
ln(popshare)	0.456***	0.472***	0.463***
	(0.068)	(0.060)	(0.116)
ln(violent_crime)	-0.074	-0.020	-0.189
	(0.112)	(0.084)	(0.160)
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)
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, as shown in subsection 2.3.1, 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. This approach is found in hate crime literature, as Gale *et al.* (2002) separate their sample into Southern and non-Southern subsamples. However, this approach decreases the number of observations and can be harmful to the model. Hence, I use a different method by adding 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 actually due to the Southern states: *gov_south*, the interaction between *south* and *gov_dem*, 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. To achieve these objectives, I constructed panel data with 47 states from 1997 to 2019. Two different approaches were used: a two-way fixed effects and a GMM-System model. The latter was used as the main model due to the use of lagged hate crimes, as used in the literature (MULHOLLAND, 2013). I find robust evidence that lagged hate crimes have a positive and significant effect on actual hate crime rates.

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 and RUSHIN, 2018), change of social norms (BURZSTYN *et al.*, 2020), and more (or less) identification with given groups (PEW RESEARCH CENTER, 2020).

I 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.

An issue to take into consideration is the definition of hate crimes and their persistent underreports. According to Levin (2015, p.1), this term has been used "since the mid-1980s to identify criminal acts motivated either entirely or in part by the fact or perception that a victim is different from the perpetrator in socially significant ways".

Thus, by considering that a hate crime is motivated by bigotry and bias, it is perceived that it is a phenomenon that occurs long before the creation of its definition. As previously shown in subsection 2.3.1, we can see that, for example, hate crimes against the African-American population have occurred throughout American history, from slavery times until nowadays. As data from the FBI (2019) shows, African-Americans are the main victims of hate crimes in the present day. In the same way, hate crimes with other different motivations have occurred previously to the definition of hate crime as well.

Although considered a historical problem, hate crimes statistics only started to be collected by the FBI in 1991, after the Hate Crime Statistics Act of 1990. As these data are voluntarily reported by local law enforcement agencies, a problem that arises is that a share of local agencies does not provide any hate crime statistics. To address this problem, I account for changes in coverage share (the *popshare* variable). However, it is important to highlight the fact that, even when a given population is covered by these statistics, there is an underestimation of hate crime incidents. It happens due to the unwillingness of victims to report and due to the difficulty of authorities in identifying the hate motivation and, consequently, reporting them as hate crime incidents (LEVIN, 2015). Hence, it is important that not only a greater share of the population is covered by these statistics but also that more efforts are made towards identifying hate crimes. More accurate statistics can offer an opportunity to better identify hate crime motivations and, consequently, more effectively confront them.

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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