Adverse labor market outcomes and hate crimes

Abstract

Given the sharp increase in hate crimes reported in the United States during the Great Recession and the coronavirus pandemic, a few studies attempted to examine the relationship between unemployment and hate crimes. Particularly, because of the strong covariance between unemployment and hate crimes observed during these latter periods. However, this study finds that those current findings remain inconclusive due to several econometric issues that are likely to cause biased estimates of the effect of unemployment on hate crimes. Given the limitations of the hate crime dataset (for example, underreporting and data gaps), we contribute to the literature by addressing econometric issues and by providing new findings concerning linkages between unemployment and hate crimes. For the period considered here, using the two-step system GMM estimator, this paper finds a nonlinear convex relationship between the hate crime rate and the unemployment rate. Additionally, we highlight the role of inertia in understanding the long-run effect of unemployment on hate crimes. Although this study is likely to suffer from precision issues due to data limitations, using fixed effects and a large sample size allow us to obtain consistent parameter estimates.

Keywords: Federal Bureau of Investigation (FBI), hate crimes, unemployment, generalized methods of moments.

1. Introduction

The Federal Bureau of Investigation (FBI) is required to enforce hate crime laws in the United States. Meanwhile, current data suggest that hate crimes are rising at an exponential pace (for example, see Figure 5 in Appendix A). While the causes of this phenomenon remain inconclusive, historical data affirm that periods of high unemployment have been associated with a moderate increase in the hate crime rate (for example, see Figure 5 in Appendix A). Meanwhile, the empirical findings concerning the relationship between unemployment and hate crimes remain inconclusive due to several factors discussed here. For policymakers, it is important to understand the extent to which unemployment affects hate crimes in order to design effective policies to improve welfare in the United States, hence the importance and motivation of this study. Therefore, using the best available data, this paper contributes to the literature by providing additional empirical findings to attenuate the uncertainty surrounding the effect of unemployment on hate crimes. For the United States, there are multiple studies that focus on hate crimes, but there are only a few studies that focus specifically on the empirical relationship between hate crimes and unemployment (Gale et al., 2002; Curhthoys, 2008; Ryan and Leeson, 2011; Anderson et al., 2020; Cai, 2021). While these previous studies provide meaningful contributions to the literature, the empirical conclusions derived from these studies remain inconclusive for the following reasons.

Firstly, those prior studies rely mainly on the static panel fixed effects model, which neglects the impact of inertia in understanding the relationship between unemployment and hate crimes. Here, this paper argues that the failure to account for the lagged dependent variable leads to an omitted variable bias if there is truly inertia in hate crimes (Fajnzylber et al., 2002). According to the literature, the persistence of hate crimes may be due to systematic inertia in the criminal justice system (McGuire, 2011), including psychological inertia (Walters, 2016).

More importantly, when there is inertia, the effect of unemployment on hate crimes is stronger in the long run. Therefore, those studies that do not consider the role of inertia in estimating the effect of unemployment on hate crimes can be viewed as inconclusive. This paper contributes to the literature by relying on a dynamic model that accounts for the effect of inertia in estimating the dynamic relationship between the unemployment rate and the hate crime rate.

Secondly, those studies that examine linkages between unemployment and hate crimes do not account for the plausibility of an endogenous relationship between unemployment and hate crimes. It is widely known that the relationship between property crime and unemployment is endogenous (Raphael and Winter-Ebmer, 2001; İmrohoroğlu et al., 2004; Lin, 2008). According to the FBI, those property crimes that are motivated by hate account for a significant proportion of aggregate hate crimes in the United States. However, Gale et al. (2002), Curthoys (2008), Ryan and Leeson (2011), and Cai (2021) do not consider the plausibility of an endogenous relationship between unemployment and hate crimes. Furthermore, apart from Cai's (2021) study, these latter studies rely on the panel fixed effects estimator, which depends fundamentally on the strict exogeneity condition. Which is likely to be violated, given the endogeneity issues that arise in modeling the dynamic relationship between the unemployment rate and the hate crime rate.

This study argues that while the case for reverse causality is weaker, the case for simultaneous causation and dynamic endogeneity is relatively stronger. Therefore, this paper selects an estimator that accounts for these types of endogeneity. The standard two-stage least squares estimator (2SLS) yields bias estimates when the endogenous lagged dependent variable enters the matrix of instruments. Whereas the two-step system GMM estimator increases consistency and efficiency, given the key moment conditions discussed by Blundell and Bond (1998), which allow the researcher to efficiently address both issues of simultaneity and dynamic endogeneity in the same empirical framework. Therefore, following Fajnzylber et al. (2002), this study proposes to rely on the two-step system GMM estimator to model the dynamic relationship between the unemployment rate and the hate crime rate. Currently, there is no study found in the empirical literature that relies on the two-step system GMM estimator to estimate the effect of unemployment on hate crimes; hence a minor contribution to the literature.

Thirdly, Gale et al. (2002), Curthoys (2008), Ryan and Leeson (2011), and Cai (2021) find contrasting results concerning the effect of unemployment on hate crimes (for example, these studies find positive and negative effects). The implication is that the effect of unemployment on hate crimes is ambiguous and likely to be nonlinear. Therefore, following Liu's (2018) theoretical suggestion, this study does not inherently assume a linear relationship. Instead, this paper tests the prospect of a nonlinear relationship between the hate crime rate and the unemployment rate. Lastly, it is widely known that the official unemployment rate can be understated, because the labor force excludes discouraged workers. Given these data misspecifications: relying solely on the unemployment rate to estimate the effect of adverse labor market conditions on hate crimes can be misleading. Moreover, the official unemployment rate is a lagging indicator, hence the importance of controlling for different proxies of unemployment.

Evidently, current studies do not consider these data issues in modeling the relationship between hate crimes and unemployment, hence another contribution made in this paper. More specifically, this study increases statistical robustness by introducing two additional variables to model adverse labor market conditions. These two additional variables are the initial unemployment claims rate and the proportion of adults out of the labor force. The initial unemployment claims rate is a leading indicator of unemployment conditions.

More importantly, during the coronavirus period, the data show that the variance of the rate of change in the initial unemployment claims rate is extensively higher than the variance of the rate of change in the actual unemployment rate. For econometric purposes, this latter finding implies that the initial unemployment claims rate may be relatively more useful in identifying large unemployment shocks in the United States, especially during periods of poor macroeconomic conditions.

Standard economic theory predicts that the loss of employment income decreases the opportunity cost of committing a crime, which increases the likelihood of engaging in more criminal activities (Ryan and Leeson, 2011). The frustration-aggression hypothesis predicts that adverse labor market outcomes can potentially lead to more aggression against the protected classes due to frustration (Dollard et al., 1939). Moreover, other theorists argue that the effect of unemployment on crime can also be negative or ambiguous (Lee, 2018). Lee's (2018) model shows that an increase in the unemployment rate reduces aggregate income and the expected return on crime, which in turn reduces the incentive to commit crimes.

In conclusion, the economic theory of crime affirms that the effect of unemployment on crime is likely to be ambiguous and influenced by key socioeconomic factors (for example, the apprehension rate, education, and aggregate income). For this study, the key empirical findings tend to be consistent with the economic theory of crime. The empirical results show a nonlinear convex relationship between the hate crime rate and the unemployment rate. For empirical robustness, this study relies on the reduced-form estimates of a panel vector autoregression (VAR) model to test the assumptions and consistency of the system GMM framework.

Firstly, the reduced-form estimates provide evidence of a dynamic simultaneous causal relationship between the unemployment rate and the hate crime rate, which indirectly supports the endogenous assumption imposed by the system GMM Model. Secondly, while the panel VAR model is specified differently in contrast to the system GMM model, the reduced-form estimates reiterate that the relationship between the unemployment rate and the hate crime rate is nonlinear and convex.

The implication is that the relationship between unemployment and hate crimes is not entirely positive as suggested by prior studies (Gale et al., 2002; Ryan and Leeson, 2011; Anderson et al., 2020; and Cai, 2021). Therefore, the nonlinear convex relationship found here is a relevant contribution to the literature. Section 2 provides a review of the literature. Section 3 provides an overview of the dataset. Section 4 reports the key findings and discusses the underlying assumptions of the two-step system GMM estimator. Section 5 tests for empirical robustness. The last section summarizes the main empirical findings.

2. Empirical literature

For the United States, there are only a few studies that examine the specific relationship between unemployment and hate crimes. Gale et al. (2002), Curthoys (2008), Ryan and Leeson (2011), and Cai (2021) find contrasting results concerning the effect of unemployment on hate crimes. Moreover, these latter studies do not account for the persistence of hate crimes or the plausibility of an endogenous relationship between unemployment and hate crimes. Gale et al. (2002) , Ryan and Leeson (2011), and Cai (2021) impose a linear functional form on the empirical relationship between unemployment and hate crimes. Whereas the economic theory of crime suggests a nonlinear relationship. Here, this study makes the following relevant contributions to literature. Firstly, this paper addresses the issues of endogeneity and functional form misspecification in estimating the relationship between unemployment and hate crimes.

Secondly, Section 3 controls for inertia and other key socioeconomic variables that are useful in understanding the relationship between hate crimes and unemployment (for example, preference for firearms, racial diversity, police activity, education, population density, and poverty). Lastly, this paper broadens the empirical literature by introducing two additional variables to capture changes in adverse labor market conditions. These two variables include the initial unemployment claims rate and the proportion of people out of the labor force.

The following studies provide additional information needed for modeling the relationship between unemployment and hate crimes. Wenger and Lentz (2021) show the relevance of inertia in understanding hate crimes in the District of Columbia. However, the latter study does not demonstrate the relevance of inertia in context of understanding the effect of unemployment on hate crimes. Here, this study contributes to the literature by showing that the impact of inertia worsens the effect of unemployment on hate crimes in the long run. Lin (2008) relies on the 2SLS estimator to estimate the endogenous relationship between unemployment and property crimes.

Lin's (2008) findings conclude that the ordinary least squares (OLS) estimator underestimates the effect of unemployment on crime. This latter finding highlights the endogeneity issue that arises in estimating the effect of unemployment on hate crimes. Particularly, because hate crimes include property crimes that are motivated by hate. For the case of Germany, Falk et al. (2011) show the relative importance of high unemployment in explaining right-wing crimes.

Raphael and Winter-Ebmer (2001) show a positive relationship between crime and unemployment in the United States. For less educated men, Gould et al. (2002) find a significant relationship between wages and crime. Hence the relative importance of incorporating a proxy for education in modeling hate crimes. Jawadi et al. (2021) investigate the relationship between unemployment and crime in Europe by relying on a time-varying vector autoregression model: they find that unemployment shocks drive crime in the United Kingdom and in France. İmrohoroğlu et al. (2004) show that strong economic performance and a higher probability of apprehension led to the decline in property crimes observed in the United States between 1980 and 1996.

Öster and Agell (2007) find a positive relationship between unemployment and property crimes in Sweden. Dustmann et al. (2011) find a positive link between unemployment and crime in the United Kingdom. Green et al. (1998) show that hate crimes are more frequent in predominantly white areas that have a high proportion of minority immigrants. This latter finding shows the importance of racial diversity in understanding bias-motivated crimes. Krohn (1976) finds that countries with high unemployment and income inequality are more likely to experience more crime. Almén (2017) shows that long-term unemployment is relatively more robust in predicting violent crimes in Sweden. Yearwood and Koinis (2011) find a negative relationship between motor vehicle thefts and unemployment. This latter finding highlights the uncertainty concerning the empirical link between crime and unemployment.

3. Empirical methodology

3.1. Data

This section presents the key empirical variables and discusses the limitations of the data. According to the FBI, a hate crime is a criminal offense that is motivated by bias against a person's race, color, disability, religion, national origin, sexual orientation, or gender identity. More importantly, a hate crime involves two components: an actual criminal offense and a bias. There is a widely held view that the FBI's hate crime data are underreported and subject to bias reporting. Depending on the severity of those latter factors, these external issues may affect the validity of the empirical estimates.

However, although hate crime data are likely to be underreported, the current available dataset does not suffer from zero reporting, which makes modeling hate crimes less challenging (for example, see the aggregate hate crime data reported in Table 5 in Appendix A). Moreover, the missing hate crime information only accounts for two percent of the data. Therefore, although the missing information and the underreporting issues are likely to affect the efficiency of the regression estimates, it is equally true that the larger sample size is likely to mitigate the effect of sampling errors on the consistency of the regressions estimates. Moreover, following a similar approach taken by Fajnzylber et al. (2002), the main empirical framework relies on state-specific fixed effects to deal with the underreporting issue. If the systematic measurement error in hate crime is due to underreporting, and it is truly time-invariant, then the two-step system GMM estimator addresses this issue relatively well (Fajnzylber et al., 2002).

On the other hand, if the measurement error in hate crime is time-varying, then it would lead to large precision issues, depending on the magnitude of the classical measurement error. In this scenario, the effect of unemployment on hate crimes is likely to be insignificant due to Type II errors caused by large classical measurement errors in the hate crime data. The essential point is that while the data limitations are valid and can affect the efficiency of the regression estimates, those limitations do not necessarily invalidate the research question or impact the ability to test the effect of unemployment on hate crimes.

Particularly, because the sample size is extremely large, and those limitations can be addressed in context of the empirical framework; assuming that the assumption made concerning the underreporting issue is valid. Which is likely to be the case, considering the stylized fact that the underreporting issue is widely viewed as a time-invariant fixed effect in the empirical literature. Nevertheless, this study reports the 95 % confidence intervals to allow the readers to determine the extent to which the precision issue is likely to affect the point estimates.

Lastly, this paper uses samples of different sizes as a means to test for the consistency of the empirical estimates. Here, it is important to standardize the hate crime data in order to obtain reliable empirical estimates that can be generalized for all the states. Therefore, the main dependent variable is measured as follows:

$$hate = \frac{aggregate\ hate\ crimes}{state\ resident\ population} \times 100,000$$

For empirical robustness, following Anderson et al. (2020), this study considers the racial crime rate as an additional dependent variable. The racial crime rate is modeled as follows

$$race = \frac{racial - motivated\ crimes}{state\ resident\ population} \times 100,000$$

Table 1 describes the key empirical variables. All the variables are state-level estimates, except the oil variable. Here, an adverse labor market outcome is defined as a state in which an individual is characterized as unemployed or out of the labor force. For econometric purposes, estimating the effect of unemployment on hate crimes requires controlling for key socioeconomic and macroeconomic factors. This study relies on the following control variables: gun ownership, arrests per capita, racial diversity, skilled labor growth, population density, oil shocks, and economic growth.

States laws on gun ownership vary significantly across the United States. The gun ownership rate captures exogenous shocks in preference for firearms. This section finds that the gun ownership rate is negatively associated with the hate crime rate. Figure 1 shows that the hate crime rate varies significantly across the United States, hence a key motivation for investigating the key factors that influence hate crimes in the United States.

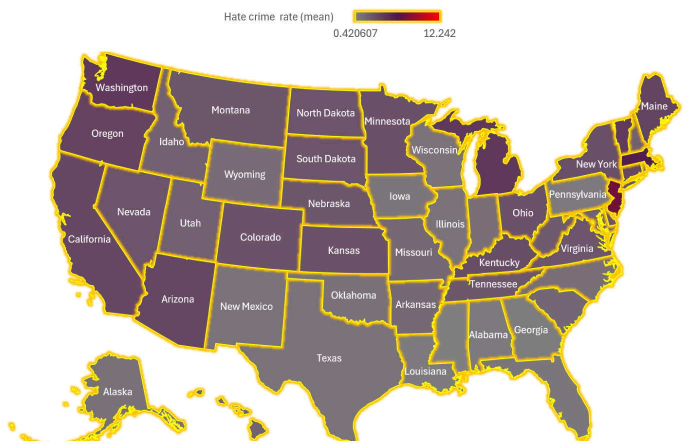


Figure 1: Annual Average Hate Crime Rate Per 100,000 (2000-2022)
Data source: Federal Bureau of Investigation, "authors calculations"

Exogenous supply shocks driven by large swings in crude oil prices affect production costs, which also affect unemployment. Additionally, this study controls for population density. Particularly, because the data show that population per square mile explains close to 60 % of the variance in the hate crime rate. Table 5 in Appendix A provides a summary of the descriptive statistics for the main variables listed in Table 1. The key covariances between the control variables and the hate crime rate are reported in Figure 5 in Appendix A. Lee (2018) shows that modeling the relationship between unemployment and crime requires controlling for other factors such as aggregate income and police activity. On one hand, this study relies on median income shocks to capture the aggregate income effect. On the other hand, this paper relies on arrests per capita as a proxy for police activity.

Moreover, the data show that historically liberal states have a higher average hate crime rate in contrast to historically conservative states. However, Figure 2 equally shows that historically liberal states experience less racial-motivated crimes per total hate crimes in contrast to historically conservative states. For instance, North Dakota has a relatively higher proportion of racial-motivated crimes in contrast to New York. Whereas New York has a relatively higher average hate crime rate in contrast to

North Dakota. Furthermore, the FBI data show that the historically liberal states such as Massachusetts, New Jersey, and the District of Columbia recorded the highest average hate crime rates between 2000 to 2022.

Variables	Description
hate	The aggregate hate crime data are public and emanate from the FBI. The aggregate hate crime index includes seven different categories of biases: racial, religion, sexual orientation, gender identity, disability, gender, and multiple. Bias-motivated crimes that fit under more than one category are included in the multiple bias category.
race	For additional robustness, this study relies on the racial crime rate as an additional dependent variable. Racial-motivated crime is the largest category of reported hate crime in the United States. The racial-motivated crime data emanate from the FBI.
out	This variable measures the proportion of adults out of the labor force. The data are collected from Bureau of Labor Statistics (BLS).
U	This variable is the official unemployment rate: it is the number of unemployed adults who are still searching for a job as a percentage of the civilian labor force. These data are collected from the Bureau of Labor Statistics (BLS).
claims	This variable is the log level of aggregate weekly initial unemployment claims. These data emanate from BLS.
claimsrate	This variable is computed by dividing aggregate initial unemployment claims by the state resident population. The formula can be described as follows: $$claimsrate = \frac{initial\ unemployment\ claims}{resident\ population} \times 100$$
guns	This variable offers state-level estimates of the gun ownership rate. The data emanate from the RAND Corporation.
pop	This index provides a robust measure of population density. It is calculated by dividing the number of state residents by the size of the state, which is measured in square miles. The data emanate from the Census Bureau.
div	The diversity index provides a measure of racial diversity. The data emanate from the Census Bureau's voting and registration data. The index is computed by relying on the annual standard deviation of the proportion of four different race groups observed during all November elections. These four racial groups include: White alone-non-Hispanic, Black alone, Asian alone, and Hispanic of any race. The variance of the four proportions is strictly less than one and a high variance indicates less racial diversity. Therefore, to compute the diversity index, this study subtracts the variance from one.
divx	This section considers a second proxy for diversity to improve robustness. This racial diversity index is measured by taking the rate of change in the proportion of minorities in different states. We first compute the proportion of the white alone population and then subtract the latter from 1. The raw data is available from the Census Bureau.
growth	This variable provides a measure of aggregate income. The growth index represents the real median income growth rate by state. The data are collected from the Census Bureau.
skilled	This variable measures the rate of change in the proportion of people in the state with a bachelor's degree or higher. The data emanate from the Census Bureau.
oil	This variable measures the rate of change in crude oil prices. Annual oil price data are collected from the US Energy Information Administration.
arrest	This variable measures the total number of police arrests per state residents. These data come from the FBI.

Table 1: Key Variables

Here, the data are organized in panel format, and the panel contains 51 cross sections: 50 states, including the District of Columbia. The frequency of the data is annual, and the range is from 2000 to 2022. For the racial diversity index (*div*):

the election data are only available every two years and relying on voter registration data may introduce systematic biases in the empirical framework.

The index is subject to data gaps, which may cause large measurement errors. There are various ways to deal with missing data (for example, one can rely on mean imputation, or multiple imputation). However, this study relies on the last observation carried forward method. Particularly, because the variance of the raw index is extremely small (for example, the variance for each state is extremely close to zero). The implication is that the data rarely changes, which means that the previous information is likely to explain a significant portion of the next observation.

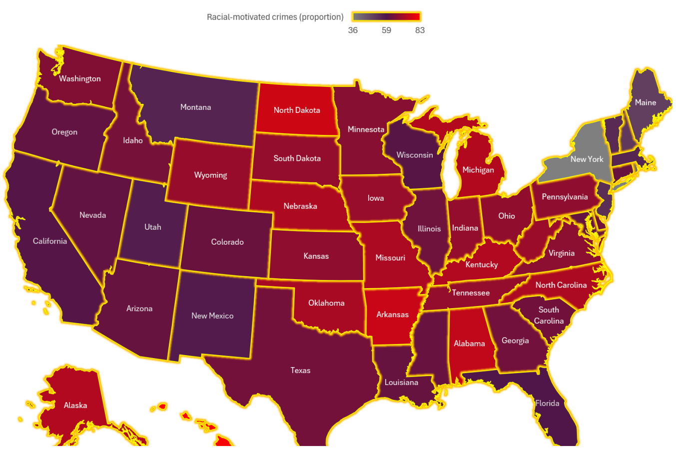


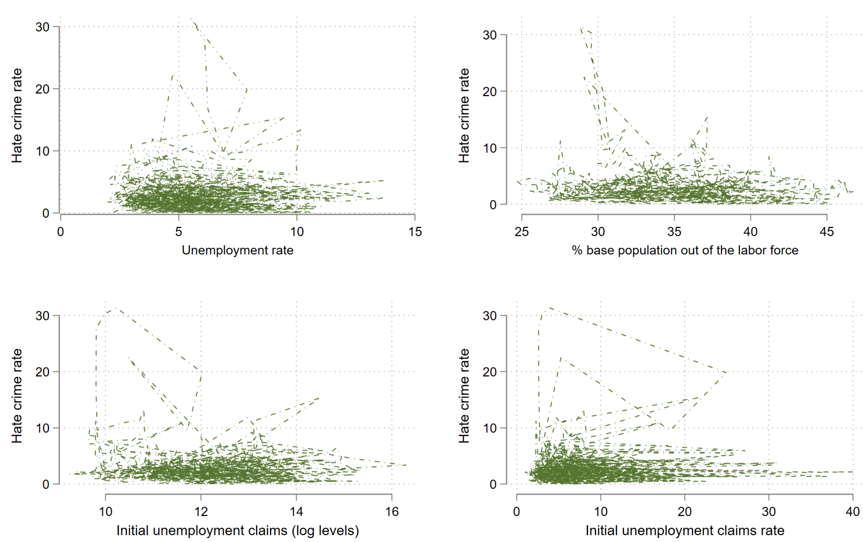
Figure 2: Racial-Motivated Crimes % Aggregate Hate Crimes (Average Proportion, 2000-2022) Data source: Federal Bureau of Investigation, “authors calculations”

Therefore, this section argues that relying on other methods such as mean imputation or multiple imputation may be more costly. Furthermore, the empirical cost of this choice does not necessarily penalize the key empirical results. Particularly, because this study relies on a second proxy for racial diversity. This alternative proxy is measured by relying on the rate of change in the proportion of minorities in each state. This additional proxy allows one to efficiently capture the effect diversity on hate crimes. Nonetheless, both measures of racial diversity are positively associated with the hate crime rate. For the two dependent variables, there are only a few missing observations for the following states: Alabama, Arkansas, Hawaii, Mississippi, and Wyoming. Nonetheless, this study relies on listwise deletion to address this issue. Mainly, because the missing data are random and only accounts for two percent of the 1,173 observations. For a small number of missing observations, the cost of multiple imputation outweighs the empirical benefits.

Furthermore, it is wise to acknowledge that there is a lack of data availability for certain key control variables that are not included in this study, but may be useful in modeling hate crimes (for example, immigration population per state, although the latter may be indirectly captured by the population density index). Nonetheless, exposing these data limitations allows the readers to better understand the challenges that arise in modeling hate crimes. Although this study is vulnerable to some data issues, the control variables are numerous, and the number of observations is extremely large. These two latter factors alleviate the impact of sampling errors on the validity of the empirical estimates.

3.2. Generalized method of moments

This section discusses the underlying assumptions of the main empirical framework. Firstly, Figure 3 reveals an ambiguous relationship between adverse labor market conditions and the hate crime rate.



Data source: "authors calculations", Federal Bureau of Investigation, Bureau of Labor Statistics

Figure 3: Adverse Labor Market Outcomes and Hate Crimes (Covariance)

For this latter reason, this section tests the prospect of a nonlinear relationship between hate crimes and adverse labor market conditions. Secondly, the lagged dependent variable is clearly endogenous and this paper argues that unemployment and hate crimes are simultaneously determined. These latter issues create some econometric problems that must be addressed in the regression model in order to obtain unbiased regression estimates.

More importantly, including the lagged dependent variable in the matrix of instruments violates the strict exogeneity condition that is required for standard econometric estimators such as the pooled OLS estimator and the panel fixed effects 2SLS estimator. Lastly, the issue of time-invariant unobserved heterogeneity must be addressed in order to avoid an omitted-variable bias. Evidently, estimating the unknown population effect of unemployment on hate crimes requires an empirical framework that can address all these latter issues, namely: simultaneous causation, the issue of time-invariant unobserved heterogeneity, and dynamic endogeneity. This section presents an estimator that can efficiently address all these latter econometric issues. Consider the following system of linear equations

$$\begin{aligned} Y_{s,t} &= \phi Y_{s,t-1} + X_{s,t}\Gamma + B_{s,t}\Lambda + \epsilon_{s,t} \\ \tilde{\triangle} Y_{s,t} &= \phi \tilde{\triangle} Y_{s,t-1} \ + \tilde{\triangle} X_{s,t}\Gamma + \tilde{\triangle} B_{s,t}\Lambda + \tilde{\triangle}\epsilon_{s,t} \end{aligned} \tag{1}$$

Where s stands for states and t denotes the time. $\tilde{\triangle}$ denotes the forward orthogonal deviations (FOD) operator. $Y_{s,t}$ is the dependent variable (for example, $hate_{s,t}$ or $race_{s,t}$) and $Y_{s,t-1}$ is the lagged dependent variable. Note that this section relies strictly on the FOD operator, particularly because it retains more information in the presence of data gaps (Arellano and Bover, 1995). $\epsilon_{s,t}$ is an error term, which comprises two components: a vector of time-invariant unobserved state-specific fixed effects (a_i) and a vector of idiosyncratic shocks (u_i). Γ is a $(K \times 1)$ vector of coefficients to be estimated and Λ is an $L \times 1$ vector of parameters to be estimated. $B_{s,t}$ is an $(N \times L)$ matrix of L exogenous variables. $X_{s,t}$ is an $(N \times K)$ matrix of K predetermined and endogenous variables.

Model (1) consists of a system of two equations: a levels equation and a forward orthogonal deviations equation. The main idea is to derive a system estimator that relies on the instruments and moments conditions of both equations. Therefore, according to (Blundell and Bond, 1998), the two-step system GMM estimator can be defined as a weighted average of the coefficients of the two equations specified in Model (1). The empirical strategy consists of estimating both equations simultaneously. For efficiency purposes, the two-step system GMM estimator relies on an optimal weighting matrix that minimizes the asymptotic variance of the estimator.

There are 51 cross sections (s) and 23 years of observations (T) for the most part (for example, see Table 5 in Appendix A). $s > T$, which is a core requirement for using the system GMM estimator. Furthermore, the system GMM estimator addresses the issue of unobserved heterogeneity more efficiently (Ullah et al., 2018): the levels equation relies on additional instruments, which are assumed to be uncorrelated with the unobserved time-invariant fixed effects over time. Whereas the forward orthogonal deviations equation directly purges the time-invariant state fixed effects. The system GMM estimator addresses the issue of endogeneity relatively more efficiently. It does not explicitly require the strict exogeneity condition for those variables that do not meet the latter condition.

Instead, it relies on weaker exogeneity conditions, which allow one to use the lags of the predetermined and endogenous variables as valid exogenous instruments. More importantly, the system GMM estimator emphasizes the use of internal instruments in modeling the endogenous and predetermined variables. This unique approach strengthens the instrument's relevance condition. On the other hand, the pooled OLS estimator and the panel fixed effects estimator tend to be less reliable when the regressors are endogenous or weakly exogenous. Furthermore, the internal validity of the empirical framework depends in part on the absence of second-order serial correlation in the error term and on the quality of the matrix of instruments (for example, the instrument relevance and exogeneity conditions must be satisfied).

This study relies on the Arellano-Bond test for serial correlation to examine the relevance of first-order and second-order serial correlation in the error term. According to Roodman (2009), first-order serial correlation is naturally expected. Whereas second-order serial correlation in the error term highlights issues in the specification of the model. Secondly, this section relies on Hansen's (1982) test of overidentification restrictions to examine the strength of the instruments (Hansen, 1982). Roodman (2009) warns about the issue of instrument proliferation. The idea is that relying on too many instruments to model the endogenous or predetermined variables may lead to bias estimates.

Consequently, Roodman (2009) argues that one should ensure that the number of instruments is lower than the number of cross sections. This can be achieved by limiting the number of lags and by collapsing the matrix of instruments as instructed by Roodman (2009).[1] This paper follows Roodman's (2009) suggestions in addressing the issue of instrument proliferation. Here, the endogenous variables are those that are simultaneously determined or subject to reverse causality. During the coronavirus pandemic, both the hate crime rate and the unemployment rate jumped simultaneously: the average hate crime rate jumped to 55% and the average un-

[1]This paper relies on Roodman's (2009) xtabond2 estimator to collapse the matrix of instruments. For replication purposes, the Roodman's (2009) xtabond2 equation for Column 1 in Table 2 can be defined as follows: xtabond2 hate l1.hate c.U##c.U pop, gmm(l1.hate pop, lag(1 9) collapse) gmm(c.U##c.U,lag(2 8) collapse) r orthogonal nodiffs small two.

employment rate increased by an additional four percent in 2020 (for example, see Figure 5 in Appendix A). Although correlation does not imply causality, the data suggest that these two shocks are highly correlated during the coronavirus pandemic. Therefore, one cannot simply reject the possibility of simultaneous causation between hate crimes and unemployment.

Evidently, hate crimes can cause individuals to lose employment or cause businesses to close, leading to a small increase in unemployment. Alternatively, failure to obtain unemployment can simultaneously lead to a small increase in hate crimes (Ryan and Leeson, 2011). For instance, according to a Nevada Current's (2023) report, the recent mass shooting that took place at the University of Nevada Las Vegas (UNLV) could have been racially-motivated and fueled by the shooter's inability to obtain employment opportunities at UNLV. Therefore, from a scientific perspective, one cannot simply conclude or assume that the relationship between hate crimes and unemployment is entirely unidirectional or purely exogenous.

Moreover, the relationship between property crimes and unemployment is subject to reverse causation (Raphael and Winter-Ebmer 2001, Lin 2008). Note that aggregate hate crimes include a significant portion of property crimes that are motivated by hate. Henceforth, this study considers the relationship between hate crimes and unemployment to be endogenous and not purely exogenous.

Concerning the types of instruments for the endogenous regressors: the system GMM approach relies strictly on internal instruments. For instance, for the levels equation, the instrument for the unemployment rate is the past lag $(t-1)$ of the first-difference of the unemployment rate. For the orthogonal deviations equation: the instruments for the unemployment rate are simply the past lags of the unemployment rate. Following Roodman (2009), this study relies on deeper lags, which means that the lag structure for the instruments of the endogenous variables starts from the second lag.

The predetermined variables are those that are assumed to be weakly exogenous, but uncorrelated with all future errors. Following Blundell and Bond (1998), the lagged dependent variable is treated as predetermined. Additionally, for econometric purposes, this section considers the following variables to be predetermined: economic growth, population density, and skilled labor growth. This latter identification is reasonable and necessary to remove any issues of reverse causation that may arise in estimating the effects of economic growth, population density, and skilled labor growth on hate crimes.

For the instruments of the predetermined variables: the system GMM approach relies strictly on internal instruments. For the levels equation, the instrument for a predetermined variable is the first-difference of the predetermined variable itself. For the orthogonal deviations equation, the instruments for the predetermined variable are the past lags of the predetermined variable. Following Roodman (2009), the lag structure for the instruments of the predetermined variables starts from the first lag.

This study treats oil shocks as strictly exogenous. Following Lee (2018), this section considers police activity (for example, arrests per capita) to be strictly exogenous. Additionally, for empirical robustness, this section considers two additional exogenous variables: racial diversity and gun ownership. This section argues that gun ownership is exogenously determined by factors that are outside of the model (for instance, preference, culture, and legislation). Lastly, racial diversity is treated as exogenous, based on the argument that the latter is also influenced by outside factors (for example, preference for location and historical migration patterns). These exogenous assumptions are widely used in the empirical literature, but they can be challenged. Some researchers may choose to treat police activity, gun ownership, and racial diversity as weakly exogenous. Nonetheless, from an empirical perspective, this study finds that treating these latter three variables as strictly exogenous or weakly exogenous makes little to no difference in the empirical estimates.

3.3. Empirical results

This section reports the main empirical estimates. Tables 2 and 3 report the p-values associated with the tests of overidentification restrictions and serial correlation. Roodman (2009) recommends using different lag structures to test the consistency of the system GMM estimates. This section follows the latter recommendation and finds that the use of different instruments does not affect the consistency of the key parameter estimates. The implication is that the key empirical results are less likely to be vulnerable to the instrument proliferation problem. Moreover, following Roodman (2009), this section ensures that the number of instruments is strictly lower than the number of cross sections.

Table 2 reports the results for the aggregate hate crime rate. Whereas Table 3 displays the results for the racial-motivated crime rate. The key empirical results in Tables 2 and 3 are highly consistent. The estimated p-values associated with the Hansen test of overidentifying restrictions are largely above five percent and below 25 percent. As suggested by Roodman (2009), these latter findings strengthen the validity of the moment conditions implied by the system GMM estimator, which are discussed extensively by Blundell and Bond (1998). The p-values associated with the Arellano-Bond test statistics show that the empirical results are less likely to be vulnerable to second-order serial correlation.

For the control variables, the key factors that explain the hate crime rate include economic growth, racial diversity, inertia, oil shocks, police activity, and the gun ownership rate. According to Lee (2018), the apprehension rate is expected to be negatively associated with crimes. This section corroborates the latter statement to some extent. Arrests per capita is negatively associated with the hate crime rate. Similar to Raphael and Winter-Ebmer's (2001) findings, this section finds that supply shocks (for example, oil shocks) are positively associated with the hate crime rate. This is likely due to the fact that negative supply shocks affect the natural rate of unemployment. An increase in real aggregate income is expected to increase the opportunity cost of committing a crime (İmrohoroğlu et al., 2004): therefore, an increase in the real median income growth rate is expected to cause a decrease in hate crimes. Here, real median income growth is found to be negatively associated with the hate crime rate: this finding is consistent with Cai's (2022) findings.

The significance of the lagged dependent variable validates the system GMM approach and provides strong evidence of the persistence of hate crimes in the United States (Wenger and Lantz, 2022). Current studies that examine the relationship between unemployment and hate crimes completely ignore the issue of inertia, which makes those latter studies inconclusive. Particularly, because the long-run effect of unemployment on hate crimes depends on inertia. The persistence of hate crimes is perhaps one of the most fundamental findings in understanding the dynamics of hate crimes in the United States. Particularly, because this scientific evidence highlights those key structural issues that affect hate crimes, which are difficult to capture with the data (for example, systematic inertia in the judicial system). Population density is highly significant in understanding hate crimes in the United States: areas that are highly dense in terms of population per square mile experience more hate crimes (for example, the District of Columbia has the highest population density index and the highest average hate crime rate in the United States).

The education proxy is not significant in explaining the hate crime rate. However, this may be due to the lack of statistical power caused by the lack of available observations. The racial diversity index ($divx$) is highly significant in understanding hate crimes. Racial diversity is positively associated with the hate crime rate. The latter result can be explained by the frustration-hatred hypothesis Dollard et al. (1939). According to Southwick (2000), access to guns enhances the art of self-defense, which improves the victim's likelihood of survival and reduces the aggressor's incentive to commit a crime. Here, this study corroborates the latter findings. The gun ownership rate is significant and negatively associated with the hate crime rate.

For the key variables of interest (for example, the adverse labor market variables), the empirical findings are highly significant and consistent with Liu's (2018) theoretical conclusions. This study finds a significant nonlinear convex relationship between adverse labor market outcomes and the hate crime rate. Figure 4 displays the relevant U-shaped relationships. The predicted values in Figure 4 emanate from Columns 2, 6, and 8 in Table 2 and Column 2 in Table 3. On one hand, below an estimated global minimum:

$$\frac{\partial hate_{s,t}}{\partial\, U_{s,t}} \equiv U^{*} \equiv \frac{.4072094}{\{2 \times .0256612\}} = 8\%$$

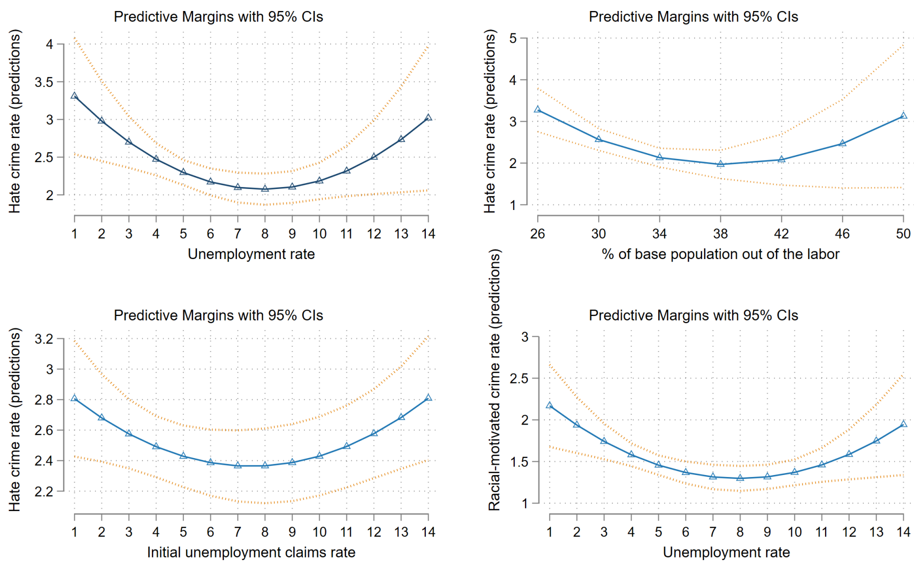
this study finds a negative association between the unemployment rate and the hate crime rate.[2] Alternatively, above the turning point, one finds the opposite effect. Where an increase in the unemployment rate leads to a significant increase in the hate crime rate. As expected, the impact of unemployment on hate crimes is significant, but relatively small, which makes more theoretical sense.

As discussed in Liu's (2018) study, the ambiguous relationship between crime and unemployment can be due to several reasons. On one hand, this study argues that at lower levels of unemployment, below the turning point: the economy is strong, workers' bargaining power is relatively stronger, and the competition for jobs is relatively lower. Therefore, a higher probability of obtaining employment coupled with strong unemployment benefits increase the opportunity cost of committing a hate crime, which reduces the incentive for hatred due to a lack of frustration (Dollard et al., 1939). Therefore, at lower levels of unemployment, as the unemployment rate increases, it is possible to observe a decrease in hate crimes. On the other hand, at higher levels of unemployment, above the turning point: the economy is below potential, and workers' bargaining power is weaker, which increases labor competition between the protected classes and the non-protected classes.

Therefore, the argument is that at excessive levels of unemployment, the low potential for employment opportunities and poor economic incentives lead to more competition, frustration, and hatred (Ryan and Leeson, 2011). Weak bargaining power, increased competition, frustration, and the low probability of obtaining employment reduce the opportunity cost of committing a hate crime. Therefore, an increase in the unemployment rate beyond the turning point is likely to cause a moderate increase in hate crimes.

[2] If one chooses Column 2 in Table 1, the turning point yields an unemployment rate of eight percent.

The confidence intervals are reported in Tables 2 and 3. Those confidence intervals reveal the uncertainty surrounding the effect of the unemployment rate on the hate crime rate. It is possible that the main empirical results may be inconsistent or vulnerable to a sample selection bias. However, this study does not find strong empirical evidence to conclude that the system GMM estimates are inconsistent or sensitive to different time samples.



Data source: "authors calculations", Federal Bureau of Investigation, Bureau of Labor Statisitics

Figure 4: Two-Step System GMM Estimates (Hate Crimes and Adverse Labor Market Outcomes) (The 95 % confidence intervals are represented by the dotted orange lines)

For instance, Tables 9 and 10 in Appendix A report the system GMM estimates for different time samples. These latter findings are highly consistent with the main empirical results found in Tables 2 and 3. Furthermore, the long-run effects of unemployment on hate crimes are reported in Table 11 in Appendix A. Given the relevance of inertia, the long-run estimates are significantly larger. For additional empirical robustness, this study relies on three additional econometric models to test the consistency of the empirical estimates. The objective of this strategy is to compare the system GMM model to other econometric approaches that are presumably less efficient and reliable. Firstly, following a similar approach taken by Raphael and Winter-Ebmer (2001), this study relies on the panel fixed effects 2SLS estimator to estimate the effect of the unemployment rate on the hate crime rate.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$
$hate_{s,t-1}$	0.708***	0.635***	0.646***	0.623***	0.593***	0.561***	0.488***	0.737***	0.515***	0.617***	0.605***	0.620***
	[0.622,0.793]	[0.472,0.797]	[0.558,0.733]	[0.546,0.700]	[0.505,0.681]	[0.355,0.768]	[0.334,0.641]	[0.445,1.028]	[0.367,0.664]	[0.547,0.687]	[0.533,0.678]	[0.493,0.746]
$U_{s,t}$	-0.462**	-0.407**	-0.389**	-0.363**								
	[-0.855,-0.070]	[-0.729,-0.085]	[-0.704,-0.074]	[-0.667,-0.059]								
$U^2_{s,t}$	0.027**	0.026**	0.020**	0.024**								
	[0.002,0.052]	[0.004,0.048]	[0.000,0.040]	[0.004,0.045]								
$pop_{s,t}$	0.001***											
	[0.001,0.001]											
$guns_{s,t}$		-0.015**				-0.018**						
		[-0.027,-0.004]				[-0.033,-0.003]						
$growth_{s,t}$			-0.014**						-0.004			
			[-0.027,-0.001]						[-0.028,0.021]			
$divx_{s,t}$				0.177**								
				[0.020,0.335]								
$out_{s,t}$					-0.319*	-0.656***						
					[-0.685,0.047]	[-1.069,-0.243]						
$out^2_{s,t}$					0.004*	0.009***						
					[-0.001,0.010]	[0.003,0.015]						
$arrest_{s,t}$					-8.631*							
					[-17.538,0.277]							
$claimsrate_{s,t}$							-0.111**	-0.158**	-0.103*			-0.083**
							[-0.204,-0.019]	[-0.311,-0.005]	[-0.217,0.011]			[-0.158,-0.008]
$claimsrate^2_{s,t}$							0.009***	0.011**	0.007**			0.005**
							[0.003,0.015]	[0.001,0.020]	[0.001,0.012]			[0.000,0.009]
$skilled_{s,t}$								-0.245				
								[-0.638,0.147]				
$claims_{s,t}$										-6.100*	-6.789*	
										[-13.377,1.178]	[-13.859,0.282]	
$claims^2_{it}$										0.239*	0.272**	
										[-0.039,0.517]	[0.006,0.539]	
$oil_{s,t}$											0.003**	0.003**
											[0.000,0.005]	[0.000,0.006]
constant	2.143***	2.743***	2.339***	2.002***	7.133**	13.887***	1.452***	1.168*	1.487***	39.463	42.930*	1.219***
	[0.923,3.364]	[1.476,4.010]	[1.110,3.568]	[0.841,3.162]	[0.605,13.660]	[6.476,21.297]	[0.776,2.129]	[-0.053,2.389]	[0.668,2.305]	[-7.848,86.773]	[-3.561,89.421]	[0.782,1.656]
# of observations	1088	769	1088	599	1088	769	1088	796	1088	1088	1088	1088
Lag structure (predetermined variables)	(1 to 9)	(1 to 5)	(1 to 10)	(1 to 11)	(1 to 8)	(1 to 3)	(1 to 2)	(1 to 1)	(1 to 2)	(1 to 1)	(1 to 13)	(1 to 12)
Lag structure (endogenous variables)	(2 to 8)	(2 to 7)	(2 to 7)	(2 to 4)	(2 to 9)	(2 to 14)	(2 to 2)	(2 to 2)	(2 to 2)	(2 to 10)	(2 to 10)	(2 to 12)
# of instruments	37	22	37	22	29	34	8	9	11	35	36	39
# of states	51	49	51	51	51	49	51	51	51	51	51	51
Arellano-Bond test for AR-1 (p-value)	0.00	0.007	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.000	0.000	0.000
Arellano-Bond test for AR-2 (p-value)	.563	.48	.539	.395	.609	.477	.661	.696	.668	.57	.558	.658
Hansen test for overidentification (p-value)	0.116	.118	.12	.187	.097	.122	.415	.13	.16	.104	.123	.198

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 2: Two-Step System GMM (All Bias-Motivated Crimes)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$	$race_{s,t}$
$race_{s,t-1}$	0.594***	0.594***	0.614***	0.637***	0.551***	0.506***	0.520***	0.601***	0.523***	0.560***	0.563***	0.556***
	[0.498,0.690]	[0.423,0.764]	[0.518,0.710]	[0.561,0.713]	[0.451,0.652]	[0.299,0.713]	[0.408,0.632]	[0.438,0.764]	[0.417,0.630]	[0.474,0.645]	[0.474,0.653]	[0.442,0.671]
$U_{s,t}$	-0.155	-0.285***	-0.138	-0.109								
	[-0.346,0.037]	[-0.498,-0.072]	[-0.372,0.096]	[-0.368,0.149]								
$U_{s,t}^2$	0.007	0.018**	0.005	0.008								
	[-0.006,0.021]	[0.003,0.032]	[-0.011,0.021]	[-0.012,0.027]								
$guns_{s,t}$		-0.006				-0.008						
		[-0.014,0.002]				[-0.018,0.003]						
$growth_{s,t}$			-0.012***						-0.001			
			[-0.021,-0.004]						[-0.013,0.011]			
$divx_{s,t}$				0.128**								
				[0.017,0.239]								
$out_{s,t}$					-0.197	-0.439***						
					[-0.539,0.144]	[-0.741,-0.136]						
$out_{s,t}^2$					0.003	0.006**						
					[-0.002,0.007]	[0.001,0.010]						
$arrest_{s,t}$					-3.830*							
					[-8.163,0.503]							
$claimsrate_{s,t}$							-0.049*	-0.096**	-0.048*			-0.044*
							[-0.104,0.006]	[-0.174,-0.019]	[-0.104,0.008]			[-0.094,0.005]
$claimsrate_{s,t}^2$							0.004***	0.007**	0.004***			0.003**
							[0.001,0.008]	[0.002,0.013]	[0.001,0.007]			[0.001,0.006]
$skilled_{s,t}$								-0.185*				
								[-0.391,0.021]				
$claims_{s,t}$										-2.541*	-3.091*	
										[-5.522,0.440]	[-6.454,0.273]	
$claims_{it}^2$										0.106*	0.128*	
										[-0.009,0.221]	[-0.002,0.258]	
$oil_{s,t}$											0.002**	0.003***
											[0.000,0.003]	[0.001,0.004]
constant	1.205***	1.738***	1.171***	0.806*	4.563	9.395***	0.792***	0.873***	0.816***	15.750	19.143*	0.723***
	[0.526,1.884]	[1.004,2.472]	[0.360,1.981]	[-0.012,1.624]	[-1.637,10.762]	[3.850,14.941]	[0.387,1.198]	[0.408,1.339]	[0.429,1.203]	[-3.465,34.966]	[-2.622,40.909]	[0.403,1.043]
# of observations	1088	769	1088	599	1088	769	1088	796	1088	1088	1088	1088
Lag structure (predetermined variables)	(1 to 12)	(1 to 10)	(1 to 10)	(1 to 7)	(1 to 8)	(1 to 3)	(1 to 2)	(1 to 1)	(1 to 1)	(1 to 15)	(1 to 13)	(1 to 1)
Lag structure (endogenous variables)	(2 to 10)	(2 to 7)	(2 to 7)	(2 to 5)	(2 to 9)	(2 to 14)	(2 to 2)	(2 to 2)	(2 to 2)	(2 to 13)	(2 to 10)	(2 to 12)
# of instruments	34	27	37	20	29	34	8	9	11	43	36	28
# of groups	51	49	51	51	51	49	51	51	51	51	51	51
Arellano-Bond test for AR-1 (p-value)	0.002	.012	0.002	0.018	0.003	.018	0.000	0.001	0.001	0.003	0.002	0.002
Arellano-Bond test for AR-2 (p-value)	.348	.80	.339	.16	.27	.85	.082	.065	.07	.194	.241	.115
Hansen test for overidentification (p-value)	.15	.106	.22	.21	.119	.107	.36	.50	.55	.169	.07	0.103

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 3: Two-Step System GMM (Racial-Motivated Crimes)

Secondly, following Anderson et al. (2020), this study relies on a dynamic panel Poisson model to examine the effect of the unemployment rate on the expected count of hate crimes (λ). Lastly, this paper replicates those past studies that rely on the panel fixed effects estimator to estimate the effect of the unemployment rate on the hate crime rate. The dynamic panel Poisson regressions are reported in Table 6 in Appendix A. The 2SLS estimates are reported in Table 7 in Appendix A. The panel fixed effects estimates are reported in Table 8 in Appendix A. The empirical findings in Tables 6 and 7 are largely consistent with the two-step system GMM estimates. However, as demonstrated in previous studies (Lin, 2008), the inability to control for endogeneity in the Panel Poisson model underestimates the effect of the unemployment rate on the hate crime rate.

For the 2SLS estimates, this study relies on the Hansen-J statistics to examine the strength of the instruments (for example, the Hansen J-statistic examines the exogeneity of the instruments or whether they are correlated with the error term). For the 2SLS estimates: the unemployment rate is instrumented by using its own lags, including the lags of oil shocks. From an empirical perspective, the diagnostic tests reported in Table 7 reiterate that the 2SLS instruments are valid.

More importantly, because the 2SLS estimates rely on less instruments, the consistency in the 2SLS estimates with respect to the system GMM estimates implies that the system GMM results are less likely to be vulnerable to the issue of instrument proliferation. Lastly, in contrast to the system GMM estimates, the panel fixed effects model shows that the effect of the unemployment rate on the hate crime rate is inconsistent and likely biased. Moreover, this study demonstrates that controlling for inertia in the panel fixed effects model improves precision and reduces the error variance (for example, the effect of the unemployment rate on the hate crime rate is largely significant in Column 7).

4. Panel vector autoregression (robustness check)

This section tests the assumptions and the robustness of the main empirical framework by relying on a panel vector autoregression (VAR) model. The panel VAR approach models each variable as a function of the other, which allows one to efficiently capture the systematic relationships between all the variables included in the system. The panel VAR model is useful to justify the endogeneity assumption imposed by the system GMM model. The panel VAR model addresses endogeneity and controls for unobserved heterogeneity by relying on the forward orthogonal transformation of the variables and by applying the GMM instrumental variable approach. Therefore, the reduced-form estimates of the panel VAR model should produce consistent and efficient reduced-form estimates that can be used to test the consistency and the assumptions of the system GMM model. Following Abrigo and Love (2016), consider the first-order panel VAR model

$$\tilde{\triangle} Z_{s,t} = \Gamma \tilde{\triangle} Z_{s,t-1} + \Lambda \tilde{\triangle} X_{s,t} + \tilde{\triangle} \epsilon_{s,t}$$

where Z denotes a (3×1) column vector of endogenous variables (for example, the unemployment rate, the quadratic term, and the hate crime rate). Γ and Λ are two (3×3) square matrices of coefficients to be estimated. $\epsilon_{s,t}$ is a composite vector that includes the idiosyncratic errors and the state-specific fixed effects. Let W denote the matrix of instruments, which includes the lags of the endogenous variables, including the exogenous oil variable. It is assumed that the oil shock is strictly exogenous and all instruments (W) are orthogonal to the errors. However, the key essential moment condition is given as follows

$$E(Z_{s,t-\rho} \cdot \tilde{\triangle} \epsilon_{s,t}) = 0, \quad \rho \geq 2$$

which implies that the deeper lags $(Z_{t-2}, Z_{t-3}, ..., Z_{t-\rho})$ are those instruments that are valid for the endogenous variables (Z_t). The reduced-form estimates are reported in Table 4.

	(1) $U_{s,t}$	(2) $hate_{s,t}$
$U_{s,t-1}$	0.998***	-0.854***
	[0.533,1.463]	[-1.405,-0.304]
$U^2_{s,t-1}$	-0.003	.0.048***
	[-0.033,0.027]	[0.014,0.083]
$hate_{s,t-1}$	0.370***	0.611***
	[0.174,0.565]	[0.352,0.869]
$oil_{s,t}$	-0.012***	0.007***
	[-0.016,-0.008]	[0.003,0.010]
# of observations	1037	1037
Lag structure (endogenous variables)	(2 to 5)	(2 to 5)

Table 4: Reduced-Form Estimates (Panel VAR)

For the panel VAR diagnostics, the unit root circle shows that the panel VAR model is stable. From an empirical perspective, Table 4 shows that there is a relevant dynamic simultaneous causal relationship between the unemployment rate and the hate crime rate. The relationship does not just run from unemployment to hate crimes, but hate crimes also affect unemployment simultaneously over time. This is another contribution to the literature on hate crimes. Additionally, the model's lag structure for the endogenous variables is consistent with the system GMM's lag structure. For the period considered here, the panel VAR estimates show that the dynamic relationship between the unemployment rate and the hate crime rate is nonlinear and convex. More importantly, this section strongly supports the endogenous assumption imposed in the main empirical framework in Section 3.

5. Conclusion

Certainly, there are some limitations to this study. These limitations emanate mainly from data issues, which are externally driven and well addressed in this paper by applying the appropriate statistical methods. For the period considered here, using the best available data and a sound empirical framework, this study finds a nonlinear convex relationship between the unemployment rate and the hate crime rate. While this contribution is strongly empirical, the econometric relevance and contribution should be considered and cannot be ignored. While developing policies based on historical data is not highly recommended, the key findings provide some meaningful insights into the historical relationship between unemployment and hate crimes.

For policy implications, an ambiguous and nonlinear relationship between unemployment and hate crimes highlights the role of economic incentives and opportunity costs in combating hate crimes. For instance, during periods of extreme unemployment, a drastic collapse in employment opportunities and workers' bargaining power can fuel animosity towards the protected classes due to the frustration induced by increased competition in the labor market (Dollard et al., 1939). Under these latter conditions, designing policies to reduce incentives for hate crimes may be useful in increasing the opportunity cost of committing a hate crime, which is likely to reduce the hate crime rate.

While this paper demonstrates the importance of socioeconomic factors in understanding hate crimes, there is currently no paper found in empirical literature other than this paper that illustrates the relevance of inertia in understanding the effect of unemployment on hate crimes in the United States. The evidence of inertia in hate crimes highlights the structural problems in the judicial system. Some studies argue that the persistence of hate crimes may be due to systematic inertia in the judicial system caused by institutional racism (Weitzer, 1996), resistance to change (Itskovich and Factor, 2023), and budget constraints (Mello, 2019). Therefore, restructuring the judicial system at the state level to incorporate laws that enhance punitive sentences for hate crimes may discourage future hate crimes and reduce the effect of inertia.

As discussed in the data section, the problem of underreporting can affect the ability of the police to collect data and fight hate crimes. Developing mechanisms to facilitate access to reporting may reduce the underreporting issue and increase public trust in the judicial system. Increasing economic incentives for investigating hate crimes and enforcing them can boost the desire for judges and officers to fight hate crimes more effectively. Ultimately, these policies would require a substantial increase in non-discretionary spending. However, it is fair to argue that the positive spillovers in society would be substantial.

This study finds a strong empirical relationship between hate crimes, population density, racial diversity, and police activity. Therefore, during periods of excessive levels of unemployment, increasing police monitoring is likely to be useful in combating hate crimes in the United States; especially in dense areas where minorities account for a sizable proportion of the state population.

Studies show that transfer payments can be useful in reducing the incentive to commit a hate crime (İmrohoroğlu et al., 2004). During the coronavirus pandemic, the hate crime rate increased significantly, although the size of unemployment benefits increased simultaneously. However, without an increase in the size of unemployment benefits, the effect of unemployment on hate crimes could have been significantly higher. While it is difficult to prove the latter hypothesis with the current dataset, theoretically, an increase in the size of unemployment benefits during periods of high unemployment compensates a sizable part of the lost income, which is likely to increase the opportunity cost of committing a hate crime (Lee, 2018).

From an empirical perspective, this paper makes numerous contributions to the literature. However, it is equally true that the empirical results are derived from aggregate data. This factor limits the scope of the study. The diagnostics and robustness tests indicate that the empirical results are consistent and robust (for example, the dynamic panel Poisson model and the 2SLS estimates yield consistent results). Nonetheless, despite the consistency in the empirical estimates: one should remain cautious in generalizing and interpreting the ceteris paribus causal effects found here. Mainly, because the underlying structure of the data or the economy may change over time, which may affect the underlying results found here. Therefore, the policy recommendations should be taken with moderation, particularly because this scientific evidence is based on historical data. Nonetheless, for the period considered here, given the sound econometric specifications, this study broadens the relevant literature and provides robust statistical evidence of a significant nonlinear convex relationship between the unemployment rate and the hate crime rate.

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Appendix A

Tables

		Mean	Std. Dev.	Min	Max	N/s/T
$U_{s,t}$	overall	5.471995	2.026432	1.991667	13.73333	1173
	between	.	1.027893	3.083696	7.209783	51
	within	.	1.752055	1.813662	12.84736	23
$claimsrate_{s,t}$	overall	6.381549	4.195433	.9664829	40.06563	1173
	between	.	1.998942	2.614294	13.64819	51
	within	.	3.698769	-.9961479	39.291	23
$out_{s,t}$	overall	34.78291	4.312381	24.66667	46.74166	1173
	between	.	3.820496	28.36413	45.28261	51
	within	.	2.067471	28.93762	40.9561	23
$claims_{s,t}$	overall	12.20963	1.176729	9.243969	16.30042	1173
	between	.	1.105831	9.87625	14.87894	51
	within	.	.4298646	10.97089	14.25477	23
$hate_{s,t}$	overall	2.65461	2.561401	.0204431	31.34473	1145
	between	.	1.947757	.420607	12.24196	51
	within	.	1.668637	-8.53848	21.75739	22.45
$race_{s,t}$	overall	1.618121	1.431702	0	16.8019	1145
	between	.	.9563996	.2347426	4.969628	51
	within	.	1.068887	-2.652262	13.4504	22.45
$growth_{s,t}$	overall	.518238	5.570956	-20.56522	18.72978	1122
	between	.	.480412	-.570462	1.948829	51
	within	.	5.550593	-20.67345	19.308	22
$pop_{s,t}$	overall	371.8576	1280.613	1.100452	10415.49	1173
	between	.	1288.36	1.230945	9208.449	51
	within	.	106.101	-496.3558	1578.894	23
$skilled_{s,t}$	overall	.5322304	.7188286	-2.199999	3.899997	816
	between	.	.1394037	.23125	1.21875	51
	within	.	.7054352	-2.092771	3.407231	16
$oil_{s,t}$	overall	6.91586	28.64749	-64.95683	55.37617	1173
	between	.	0	6.91586	6.91586	51
	within	.	28.64749	-64.95683	55.37617	23
$guns_{s,t}$	overall	38.88929	13.63519	3.4	69.4	850
	between	.	13.48929	9.294118	63.65882	50
	within	.	2.717828	30.70694	49.59518	17
$div_{s,t}$	overall	.6459578	.0825219	.5052504	.8475404	1173
	between	.	.0808265	.5186648	.8204183	51
	within	.	.0199891	.5718488	.7156165	23
$arrest_{s,t}$	overall	.0425439	.0203123	0	.3679128	1173
	between	.	.0133411	.004521	.0688965	51
	within	.	.0154256	-.0164063	.3529624	23
$divx_{s,t}$	overall	.463619	.9432701	-2.616072	5.289137	612
	between	.	.2850601	-.2376303	1.431566	51
	within	.	.899979	-1.914822	4.896041	12

Table 5: Summary Statistics (Panel Data)

Robustness Check

	(1)	(2)	(3)	(4)
	$\lambda_{s,t}$	$\lambda_{s,t}$	$\lambda_{s,t}$	$\lambda_{s,t}$
$count_{s,t-1}$	0.001***	0.001***	0.001***	0.001***
	[0.000,0.001]	[0.001,0.001]	[0.001,0.001]	[0.000,0.001]
$U_{s,t}$	-0.133**			
	[-0.236,-0.030]			
$U^2_{s,t}$	0.008**			
	[0.001,0.015]			
$oil_{s,t}$	0.001**		0.002***	
	[0.000,0.002]		[0.001,0.003]	
$out_{s,t}$		-0.249*		
		[-0.511,0.013]		
$out^2_{s,t}$		0.004*		
		[-0.000,0.007]		
$arrest_{s,t}$		-4.961*		
		[-10.072,0.149]		
$claimsrate_{s,t}$			-0.021*	
			[-0.044,0.003]	
$claimsrate^2_{s,t}$			0.001***	
			[0.000,0.002]	
$U_{s,t-1}$				-0.136***
				[-0.206,-0.066]
$U^2_{s,t-1}$				0.008***
				[0.004,0.012]
# of observations	1088	1088	1088	1088

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 6: Dynamic Panel Poisson Model (Hate Crimes)

	(1) $hate_{s,t}$	(2) $hate_{s,t}$	(3) $race_{s,t}$	(4) $race_{s,t}$
$U_{s,t}$	-0.704***	-0.477***	-0.270***	-0.357**
	[-1.164,-0.244]	[-0.777,-0.176]	[-0.440,-0.100]	[-0.654,-0.060]
$U_{s,t}^2$	0.040**	0.028***	0.015***	0.019*
	[0.009,0.071]	[0.009,0.047]	[0.004,0.026]	[-0.002,0.039]
$hate_{s,t-1}$		0.695***		
		[0.598,0.792]		
$races_{s,t-1}$			0.636***	
			[0.537,0.735]	
constant	5.167***	2.509***	1.564***	2.945***
	[3.658,6.677]	[1.569,3.448]	[1.008,2.119]	[1.990,3.900]
# of observations	1096	1088	1088	1096
Hansen J statistic Chi-square (P-value)	0.38	.99	0.2381	0.1744
# of instruments	4	5	5	4

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 7: Dynamic Panel Fixed Effects 2SLS Model (Second Stage)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$	$hate_{s,t}$
$U_{s,t}$	-0.085**					-0.174	-0.433**
	[-0.152,-0.019]					[-0.447,0.099]	[-0.797,-0.069]
$out_{s,t}$		-0.055			-0.676		
		[-0.163,0.053]			[-1.566,0.215]		
$claimsrate_{s,t}$			0.038***	0.033			
			[0.014,0.061]	[-0.019,0.086]			
$claimsrate^2_{s,t}$				-0.001			
				[-0.002,0.001]			
$pop_{s,t}$				0.010***	0.010***	0.010***	0.017***
				[0.010,0.010]	[0.010,0.010]	[0.010,0.010]	[0.016,0.019]
$growth_{s,t}$				-0.015***	-0.019**	-0.022***	-0.005
				[-0.026,-0.004]	[-0.033,-0.004]	[-0.035,-0.009]	[-0.020,0.011]
$skilled_{s,t}$				0.110	0.136	0.143	0.149
				[-0.097,0.317]	[-0.041,0.312]	[-0.035,0.321]	[-0.138,0.436]
$out^2_{s,t}$					0.010		
					[-0.002,0.022]		
$U^2_{s,t}$						0.010	0.034**
						[-0.009,0.028]	[0.007,0.061]
$hate_{s,t-1}$							-0.180**
							[-0.319,-0.042]
$divx_{s,t}$							0.283**
							[0.042,0.524]
constant	3.123***	4.557**	2.413***	-1.557***	10.330	-0.749*	-2.771***
	[2.759,3.487]	[0.810,8.304]	[2.263,2.564]	[-1.813,-1.301]	[-6.194,26.853]	[-1.566,0.068]	[-3.724,-1.818]
# of observations	1145	1145	1145	802	802	802	589

Table 8: Panel Fixed Effects Model

	(1) $hate_{s,t}$	(2) $hate_{s,t}$	(3) $hate_{s,t}$	(4) $hate_{s,t}$	(5) $hate_{s,t}$	(6) $hate_{s,t}$	(7) $hate_{s,t}$	(8) $race_{s,t}$	(9) $race_{s,t}$	(10) $race_{s,t}$	(11) $race_{s,t}$	(12) $race_{s,t}$
$hate_{s,t-1}$	0.711***	0.637***	0.727***	0.716***	0.853***	0.866***	0.562***					
	[0.463,0.959]	[0.475,0.800]	[0.394,1.059]	[0.444,0.988]	[0.635,1.070]	[0.605,1.127]	[0.356,0.768]					
$U_{s,t}$	-0.371**	-0.357**	-0.475***	-0.373**	-0.365***			-0.254**	-0.015	-0.210**		
	[-0.669,-0.074]	[-0.704,-0.011]	[-0.754,-0.196]	[-0.657,-0.089]	[-0.592,-0.137]			[-0.489,-0.020]	[-0.225,0.194]	[-0.410,-0.011]		
$U^2_{s,t}$	0.023**	0.023*	0.028***	0.022**	0.021**			0.015*	0.001	0.012*		
	[0.002,0.044]	[-0.001,0.046]	[0.009,0.047]	[0.002,0.041]	[0.005,0.038]			[-0.002,0.032]	[-0.013,0.016]	[-0.002,0.027]		
$guns_{s,t}$		-0.015**					-0.017**					-0.007
		[-0.026,-0.003]					[-0.032,-0.002]					[-0.018,0.004]
$growth_{s,t}$			-0.012**								-0.015***	
			[-0.020,-0.003]								[-0.024,-0.007]	
$div_{s,t}$				1.195								
				[-1.249,3.640]								
$pop_{s,t}$					0.000**					0.000***		
					[0.000,0.001]					[0.000,0.000]		
$claimsrate_{s,t}$						-0.151***					-0.087**	
						[-0.259,-0.043]					[-0.171,-0.003]	
$claimsrate^2_{s,t}$						0.008***					0.004**	
						[0.003,0.013]					[0.000,0.008]	
$skilled_{s,t}$						0.002						
						[-0.222,0.226]						
$out_{s,t}$							-0.602***					-0.401**
							[-1.015,-0.190]					[-0.705,-0.097]
$out^2_{s,t}$							0.008**					0.005**
							[0.002,0.014]					[0.001,0.009]
$race_{s,t-1}$								0.586***	0.877***	0.787***	0.479***	0.504***
								[0.401,0.771]	[0.729,1.025]	[0.562,1.011]	[0.243,0.715]	[0.299,0.709]
$divx_{s,t}$									0.211**			
									[0.041,0.382]			
constant	1.974***	2.528***	2.351***	1.282	1.583***	0.821*	12.937***	1.463***	0.143	1.012***	1.113***	8.746***
	[0.986,2.963]	[1.191,3.865]	[0.986,3.716]	[-0.827,3.392]	[0.695,2.470]	[-0.127,1.770]	[5.529,20.345]	[0.648,2.278]	[-0.607,0.894]	[0.281,1.743]	[0.703,1.523]	[3.154,14.338]
# of observations	736	721	736	736	736	444	721	736	247	736	736	721
Lag structure (predetermined variables)	(1 to 5)	(1 to 5)	(1 to 12)	(1 to 18)	(1 to 5)	(1 to 3)		(1 to 3)	(1 to 3)	(1 to 3)	(1 to 2)	(1 to 3)
Lag structure (endogenous variables)	(2 to 9)	(2 to 7)	(2 to 5)	(2 10)	(2 to 11)	(2 to 6)	(2 to 14)	(2 to 7)	(2 to 7)	(2 to 7)	(2 to 2)	(2 to 14)
# of instruments	25	22	37	38	35	21	34	19	20	23	11	34
# of states	50	49	50	50	50	50	49	50	50	50	50	49
Arellano-Bond test for AR-1 (p-value)	0.001	0.007	0.004	0.002	0.003	0.00	0.01	0.002	0.002	0.004	0.002	0.017
Arellano-Bond test for AR-2 (p-value)	.59	.474	.50	.58	.65	.76	.47	.48	.49	.25	.193	.85
Hansen test for overidentification (p-value)	.114	.113	.30	.14	.25	.23	.12	.12	.117	.21	.19	.106

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 9: Two-Step System GMM (2000-2015)

	(1) $hate_{s,t}$	(2) $hate_{s,t}$	(3) $hate_{s,t}$	(4) $hate_{s,t}$	(5) $hate_{s,t}$	(6) $hate_{s,t}$	(7) $hate_{s,t}$	(8) $race_{s,t}$	(9) $race_{s,t}$	(10) $race_{s,t}$	(11) $race_{s,t}$	(12) $race_{s,t}$
$hate_{s,t-1}$	0.602***	0.731***	0.616***	0.595***	0.656***	0.737***	0.592***					
	[0.512,0.693]	[0.603,0.859]	[0.526,0.705]	[0.492,0.698]	[0.616,0.697]	[0.445,1.028]	[0.391,0.793]					
$U_{s,t}$	-0.300*	-0.423***	-0.336**	-0.378**	-0.302*			-0.110	-0.096	-0.115		
	[-0.612,0.013]	[-0.655,-0.192]	[-0.657,-0.015]	[-0.739,-0.017]	[-0.627,0.024]			[-0.301,0.082]	[-0.320,0.129]	[-0.327,0.098]		
$U^2_{s,t}$	0.016	0.026***	0.019*	0.026**	0.015			0.005	0.007	0.007		
	[-0.004,0.037]	[0.011,0.042]	[-0.003,0.040]	[0.001,0.050]	[-0.005,0.036]			[-0.009,0.018]	[-0.010,0.023]	[-0.008,0.021]		
$guns_{s,t}$		-0.012**					-0.014*					-0.004
		[-0.021,-0.002]					[-0.028,0.001]					[-0.013,0.005]
$growth_{s,t}$			-0.018**								-0.012*	
			[-0.032,-0.004]								[-0.024,0.000]	
$divx_{s,t}$				0.228***					0.148**			
				[0.063,0.393]					[0.037,0.259]			
$pop_{s,t}$					0.001***					0.000***		
					[0.001,0.001]					[0.000,0.000]		
$claimsrate_{s,t}$						-0.158**					-0.086***	
						[-0.311,-0.005]					[-0.142,-0.029]	
$claimsrate^2_{s,t}$						0.011**					0.004**	
						[0.001,0.020]					[0.001,0.007]	
$skilled_{s,t}$						-0.245						
						[-0.638,0.147]						
$out_{s,t}$							-0.568**					-0.422*
							[-1.095,-0.041]					[-0.900,0.057]
$out^2_{s,t}$							0.008**					0.006*
							[0.000,0.015]					[-0.001,0.012]
$race_{s,t-1}$								0.610***	0.614***	0.671***	0.609***	0.553***
								[0.507,0.712]	[0.528,0.700]	[0.609,0.733]	[0.462,0.756]	[0.319,0.788]
constant	2.100***	2.462***	2.204***	2.102***	1.864***	1.168*	11.766**	1.040***	0.780**	0.772**	0.940***	8.501*
	[0.891,3.310]	[1.485,3.440]	[1.052,3.356]	[0.670,3.534]	[0.679,3.049]	[-0.053,2.389]	[1.879,21.652]	[0.338,1.742]	[0.002,1.559]	[0.132,1.413]	[0.558,1.323]	[-0.521,17.522]
# of observations	892	577	892	599	892	796	577	892	599	892	892	577
Lag structure (predetermined variables)	(1 to 5)	(1 to 5)	(1 to 3)	(1 to 3)	(1 to 10)	(1 to 1)	(1 to 3)	(1 to 10)	(1 to 3)	(1 to 1)	(1 to 1)	(1 to 6)
Lag structure (endogenous variables)	(2 to 9)	(2 to 7)	(2 to 7)	(2 to 7)	(2 to 10)	(2 to 2)	(2 to 14)	(2 to 10)	(2 to 7)	(2 to 7)	(2 to 4)	(2 to 14)
# of instruments	25	22	23	20	37	9	34	32	20	23	13	37
# of states	51	49	51	51	51	51	49	51	51	51	51	49
Arellano-Bond test for AR-1 (p-value)	0.00	0.005	0.00	0.00	0.00	0.00	0.00	0.00	0.02	0.003	0.001	0.01
Arellano-Bond test for AR-2 (p-value)	.552	.43	.54	.39	.58	.69	.45	.28	.172	.23	.11	.75
Hansen test for overidentification (p-value)	0.15	.47	.07	.135	.175	.13	.39	.17	.167	.10	.38	.23

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

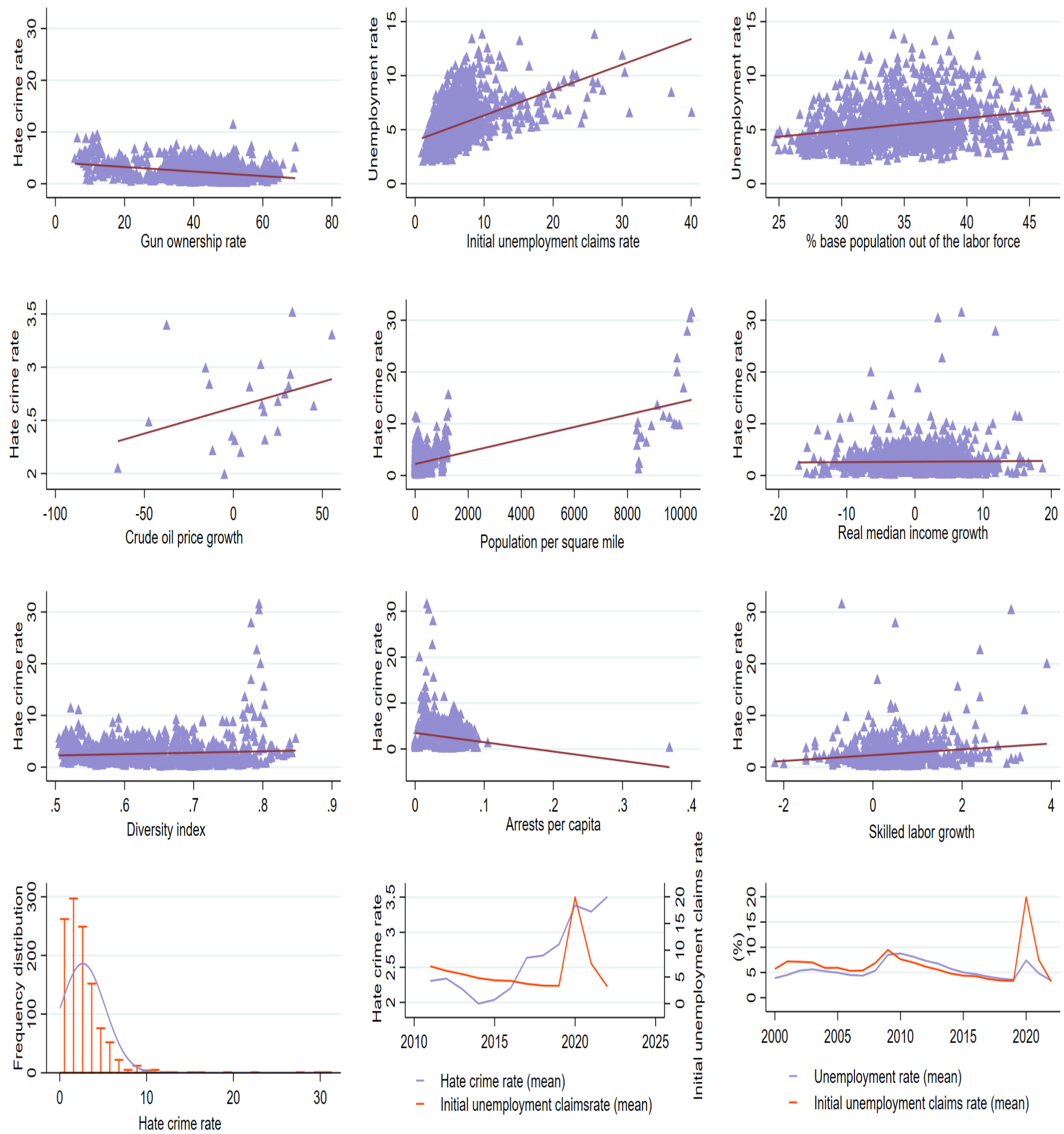
Table 10: Two-Step System GMM (2005-2022)

	(1) $hate_{s,t}$	(2) $hate_{s,t}$	(3) $hate_{s,t}$	(4) $hate_{s,t}$	(5) $race_{s,t}$	(6) $race_{s,t}$	(7) $race_{s,t}$	(8) $race_{s,t}$
$U_{s,t}$	-1.582523 **	-1.114424**	-1.097356**	-.9627822**	-.380829	-.7024284**	-.3582556	-.3013144
	[-3.160275,-.0047718]	[-2.134587 , -.0942607]	[-2.015876,-.1788359]	[-1.714556 ,-.2110083]	[.8479257,.0862677]	[-1.336162,-.0686953]	[-.9562897,.2397785]	[-.966778, .3641492]
$U_{s,t}^2$	.0912959*	.0702279**	.0570253*	.064983 *	.0179117	.0439801**	.0133768	.0210267
	[-.0073694,.1899612]	[.0017756, .1386803]	[-.0002948,.1143454]	[.0127401 ,.1172259]	[-.0156216 , .0514449]	[.0017783,.0861819]	[-.0275145,.0542681]	[-.029629,.0716824]
# of observations	1088	769	1088	599	1088	769	1088	599

95 % confidence interval in brackets
* $p < 0.10$, ** $p < 0.05$, *** $p < .01$

Table 11: Two-Step System GMM's Long-Run Estimates (Impact of Unemployment on Hate Crimes)

Figures



Data source: "authors calculations", Bureau of Labor Statistics, Federal Bureau of Investigation, Rand Corportation, Census Bureau

Figure 5: Data Visualization (Key Variables)