



Evaluating the existence of a natural U.S. hate crime rate using a fractional integration approach

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Abstract

We assess the degree of persistence for 36 U.S. states' hate crime rates using fractional integration. For 9 states the hate crime rate exhibits mean reversion. The hate crime rate tends to an upward trend for 5 states (possibly reflecting increased hate crime reporting/compliance through time) and for 3 states there is evidence that the hate crime rate reverts to a downward trend. This is consistent with an evolving natural rate over the sample for these 8 states. For 17 states law enforcement expenditures aimed at deterrence will at best lower offending in the short run because the hate crime will return to its constant or evolving natural rate in the long run. Corrective policies designed to change the natural rate are recommended for these states. The results for the District of Columbia and Utah are ambiguous, and for the remaining 17 states there is no reversion to a natural hate crime rate.

Keywords Hate crime · Time-series · Persistence · Fractional integration · U.S. states

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1 Introduction

Hate crime involves hostility or bias aimed at an individual's religion, national origin, disability, or race. The victim of hate crime does not need to have the characteristics that the hostility is aimed at and hate crime can be perpetrated directly towards a person (through physical assault, verbal abuse and incitement to hatred) or property. Hate crimes usually entail more violent acts than necessary to harm the victim because aggressors perpetrate acts to send a message to the victim in addition to expressing hatred or anger against them. Hate crime is increasingly being acknowledged as a major category of crime in several jurisdictions. Hate crimes are frequently recorded in advanced countries and victims are usually minorities and immigrants (Gray and Hansen 2021).

Partly due to the prevalence of hate crimes, social movements have emerged with an anti-hate crime focus. Moreover, several nations currently have hate crime laws with severe punishments (Mellgren et al. 2021). A growing number of papers have addressed a variety of its features. These include, the determinants of hate crimes (Ryan and Leeson 2011; Basu 2021; Cikara et al. 2022; Bhai Patel et al. 2024), the economic and social impact of hate crime (Sullivan et al. 2016; Mellgren et al. 2021; Petach and Rumbaugh 2024) and the measurement of hate crime, hate crime reporting, and the legal framework for hate crimes (Stacey 2015; Farrell and Lockwood 2023; Mills et al. 2024; Vergani et al. 2024).

However, several aspects of hate crimes have not been examined in the literature. This includes the persistence of hate crimes, which is important to determine whether a natural rate of hate crime exists (Buck et al. 1983, 1985). Reversion of the hate crime rate to a mean or trend is consistent with Medoff's (1999) theory of hateful behaviour and is an indication of the existence of a natural rate of hate crime. The existence of a natural rate of hate crime suggests that any shocks to hate crime will be temporary. This implies that law enforcement expenditures can only cause transitory deviations from the natural hate crime rate and that the hate crime rate will return to its equilibrium (natural rate) in the long-run.

Hate crime rates that revert to a linear trend suggest an evolving (rather than constant) natural rate whereby the impact of crime prevention measures will be temporary. This will be a particular cause of concern for policy makers when the trend is upwards and indicates a genuine systematic rise in the natural hate crime rate. However, positive trend hate crime reversion may instead reflect an increase in hate crime reporting/compliance through time, which Dugan and Chenoweth (2020) find evidence of in the U.S. between 1992 and 2012. Further, the implication of linearly trended hate crime rates deterministically rising or falling forever may be unrealistic, for example, hate crime rates cannot go below zero and improved reporting/compliance will eventually achieve a maximum. Hence, trend reversion will be interpreted as an approximation to the sample that we employ and may indicate a natural hate crime rate that genuinely evolves through time or, in the case of upward trend reversion, reflect rising hate crime reporting/compliance through time. Nevertheless, we distinguish a natural hate crime rate that reverts to a constant mean from one that reverts to a trend.

The existence of hate crime persistence indicates that a natural rate of hate crime does not exist. This is consistent with the hypothesis of hysteresis in crime rates which asserts that any shocks to hate crime will be permanent. In this case, deterrent measures can be used to reduce hate crimes in the long run such as the imposition of longer jail terms and more rigid bail conditions for offenders. The crime hysteresis hypothesis suggests that increased government spending on police activities can be employed to combat hate crime, especially in states, communities or countries experiencing exceptionally high hate crime rates.

The aim of this study is to analyze the degree of persistence and trends in hate crime rates across U.S. states for the period 1993–2022. While the previous literature has tested for a natural rate in various crime rate measures no such tests have been conducted for the hate crime rate. Hence, the first contribution of our paper is to empirically test the natural rate hypothesis for the hate crime rate, being that the hate crime rate tends to a constant equilibrium level (a constant natural rate), reverts to a trend (depicting an evolving natural rate through time), or whether the hate crime rate does not tend to an equilibrium (thereby exhibiting hysteresis). The previous literature has also tested for a natural rate in crime rates for the whole U.S. however it has not done so for each individual U.S. state and has not, therefore, been able to identify any heterogeneity across states. The second contribution of our paper is to test the natural rate hypothesis for 36 individual U.S. states' hate crime rates. The third contribution of our paper is in our use of fractional integration methods, which provide more flexibility in determining the degree of persistence in the data than standard methods used in the literature based on integer orders of integration. We use a method that is the most efficient against reasonable alternatives, therefore making it more precise in the estimation of model parameters.

We concentrate on U.S. states for the following reasons. Hate crimes are increasing in several U.S. states. According to *Crime Data Explorer* of the Federal Bureau of Investigation (CDEFBI), the reported number of hate crime incidents rose from 11,129 cases in 2020 to 13,377 cases in 2022. These figures are equivalent to hate crimes rates (defined as the number of reported cases per 100,000 persons) rising from 3.357 in 2020 to 4.018 in 2022. Many U.S. hate crimes occurred in populated areas or areas regularly visited by multiple people. According to CDEFBI, 26.8% of hate crime incidents in 2022 took place near residences/homes while another 15.7% of hate crime incidents occurred on roads/highways/streets/alleys/sidewalks. According to CDEFBI about two-thirds of hate crime incidents in 2022 were committed against people, which demonstrates that most U.S. hate crimes are committed against people (rather than property).

The rest of the paper is organized as follows. Section 2 presents the literature review while Sect. 3 outlines the methodology. Section 4 discusses the data and Sect. 5 examines the empirical results. Section 6 concludes.

2 Literature review

Ehrlich (1973) tests whether raising the penalties of committing crime reduces crime rates (called deterrent effects). The evidence presented suggests that many crimes against property are viewed as worth the risk because the expected marginal gains exceed the expected marginal costs. Hence, raising the expected marginal costs to perpetrators through increased policing measures has a deterrent effect. This paper also found that “absolute magnitudes of the estimated elasticities of specific crimes with respect to estimates of probability and severity of punishment are not inconsistent with the hypothesis that law-enforcement activity has a deterrent effect on offenders, which is independent of any preventive effect of imprisonment. Moreover, the elasticities associated with crimes against the person are not found to be lower, on the average, than those associated with crimes against property.” Ehrlich (1973, p. 560). The estimates further suggest that the marginal cost of police and court measures against criminals are less than the increased marginal revenue (via lower social loss from crime) hence making these measures effective.

However, Narayan et al. (2010) suggest that empirical evidence in the subsequent literature that they reviewed is mixed regarding the presence of a deterrent effect. One economic reason why there may be no long run deterrent effect is that there is a natural rate of crime. Buck et al. (1985) suggest that while increased law enforcement expenditure can reduce the property crime rate in the short run it will have no effect on the long run property crime rate, which returns to its natural rate. This is analogous to the well-known Phillips Curve theory that gives rise to the notion of a natural rate of unemployment. In terms of property crime, it is postulated that there is a group of potential criminals where the marginal returns of an additional unit of legal activity are diminishing. For this group the expected benefits of crime are so large that any realistic increase in law enforcement expenditure will not deter their participation in crime in the long run. This group includes the long term unemployed, unskilled workers at the lower end of the income distribution as well as those with drug and gambling addictions. Buck et al. (1983) contend that the natural rate of crime hypothesis is applicable to all types of profit motivated property crime, such as burglary, larceny, automobile theft and robbery.

Narayan et al. (2010) argue that this model can be extended to crimes against the person that result from property crime. For example, assault or murder can often result from a property crime when the perpetrator is caught in the act, hence providing a justification for a natural rate in these types of crime. Similarly, the gains to drug-related crimes may be so high that they are immune to deterrent effects and such crimes, as well as any violent crimes against people arising from such drug-related activity, may also have a natural rate. Another possible rationale for a natural rate in crimes against the person is when they are “crimes of passion” (such as homicide and rape) which may be less likely to be deterred by law enforcement activity (see, Withers 1984, p. 179). A similar non-profit rationalisation for a natural crime rate is that it is determined by “... the social characteristics of the population and the economic tension within the locality. These factors produce a pool of individuals who are potential criminals. The individuals possess or have developed demoralization costs toward society.” Buck et al. (1985, pp. 257–258).

Black (1983) suggests that most homicides and assaults as well as some burglaries in the U.S. may be regarded as the self-help form of social control, being unilateral acts of violence, theft or destruction that are justified as punishment for a perceived wrong-doing. Perceived wrong-doings may be based on collective responsibility whereby any person within a group (defined by factors such as ethnicity, location, race or social class) may be held to account for the actions of others.¹ As Black (1983, p. 38) states, "... for instance, a black rapist described his selection of white victims as a process of vengeance against white people in general ...". To the extent that hate crimes can be considered self-help (whether carried out in the heat of passion or coldly planned) they may have a natural rate because they are largely impervious to deterrent due to the perpetrator's belief that their actions are warranted (possibly being a matter of honour). "To the degree that people feel morally obligated to commit crimes, it would seem that the capacity of the criminal law to discourage them - its so-called deterrent effect - must be weakened. ... In fact, one former resident of Harlem has noted that the inhabitants of that unusually violent area appear to debate in their own minds whether or not moralistic homicide is ultimately worth its legal consequences That the desirability of killing another person is entertained at all is remarkable, however, particularly when the death penalty is believed to be a possible result ... Furthermore, since other crimes of self-help carry fewer risks of a legal nature, they should be even harder to discourage than homicide." Black (1983, p. 39).

We argue that some hate crimes may be considered a "crime of passion", the result of "demoralization costs toward society" or the self-help form of social control and thereby have a natural rate. However, it would be unwise to assume that social characteristics of populations and economic tensions are the same in different locations, hence the associated "demoralization costs to society" can potentially vary across states. Similarly, "crimes of passion" or the propensity to engage in self-help may not be evenly distributed across states. To the extent there are such variations, this may help explain why some states have natural hate crime rates while others do not. Conversely, other hate crimes may be rationally planned and be subject to deterrent effects. While many hate crimes may not provide a direct monetary gain, they will

¹ Lickel et al. (2006) develop the notion of collective responsibility in their discussion of vicarious retribution within the context of inter-group conflict. Vicarious retribution is where an in-group member performs a hostile act against out-group members in retaliation for harmful behaviour towards other in-group members even though they were not adversely treated themselves. Further, the out-group members who are subject to the hostile act may not be responsible for the original aggressive act towards the person's in-group members. "For example, in U. S. history, White violence toward Blacks often occurred as a result of a provocation (often itself imagined rather than real) from one Black person toward a White individual." Lickel et al. (2006, p. 373). In many such cases the Blacks subjected to the violence may have had little, if any, connection to the original (real or imagined) provocation. Therefore, vicarious retribution (that is often regarded as morally justified by the perpetrator(s)) may provide a source of racially (and otherwise) motivated U.S. hate crime within an inter-group context. Decategorization is suggested as one means of resolving vicarious retribution by distinguishing group members as individuals rather than viewing them as part of a whole homogeneous group. "For example, the week after the 9–11 attacks, in response to concern about the possible rise of hate crimes against Muslims, President Bush (2001) gave a widely publicized address in which the major thrust was for Americans to make a clear distinction between the 9–11 hijackers and Muslim-Americans. ... In essence, Bush was saying that not all Muslims are like the 9–11 hijackers and are therefore not to be blamed or harmed in revenge. Thus, one of the critical features of decategorization in the early stages of a conflict is that it may counteract the aggression-producing effects that can arise from perceiving the outgroup as unified and undifferentiated" Lickel et al. (2006, p. 384).

yield the perpetrator satisfaction or utility more broadly. To the extent that the perpetrator derives utility from hate crime the economic model of rational choice discussed above can be applied to it. Hence, the perpetrator may be characterised as engaging in hate crime provided the expected (marginal) utility derived from the act is perceived as worth the expected (marginal) cost.² That is, the hate crime will be committed when it is considered worth the risk of apprehension and subsequent sanction.

We intend to test the three competing hypotheses of whether hate crimes have a constant natural rate, a natural rate that evolves around a trend or are subject to deterrent effects (exhibit hysteresis). To do this we follow the literature that employs unit root and stationarity tests to the unemployment rate to determine whether there is a natural rate of unemployment. When such tests indicate that the unemployment rate does not have a unit root a natural rate of unemployment is inferred whereas finding a unit root in this series is indicative of unemployment hysteresis (see, for example, Omay et al. 2021). Analogously, if the hate crime rate does not have a unit root this provides evidence of the existence of a natural hate crime rate while finding a unit root in this series suggests hysteresis in the hate crime rate and that there is a deterrent effect. The policy implications are that increased law enforcement expenditures will have a long run impact on hate crime if the evidence supports the hysteresis hypothesis. However, if there is a natural hate crime rate, while such spending may reduce offences in the short run it will have no long run effect because hate crimes will return to their natural rate. In this case "... instead of spending more on law enforcement, which will have no effect on the long-run crime rate, governments should consider policies that affect the economic and social structural factors that determine the crime rate in the long run." Narayan et al. (2010, p. 779). Hence, policies that attempt to correct criminals' behaviour by addressing their motives should be implemented in an attempt to change (lower) the natural rate of hate crime. These include policies aimed at educating potential offenders and rehabilitating convicted criminals. To the extent that hate crime is the result of deprivation, policies designed to reduce poverty and inequality may also be considered.

Narayan et al. (2010) suggest that earlier evidence in the literature on the deterrent effect of crime prevention policies was mixed. They applied unit root tests that allow for structural breaks and obtained the following findings for U.S. data over the period 1960–2006. Crime rates for assault, motor vehicle theft, and the violent crime index cannot reject the natural rate hypothesis. However, the following U.S. crime rates were found to be consistent with the hysteresis hypothesis: total aggregate crime, burglary, murder, property theft index, rape, robbery, and theft. A natural rate was supported for the following UK crime rates (using a 1898–1999 sample period): total crime, burglary, criminal damage, robbery, theft, and violent crimes. Whereas a natural rate was rejected in favour of the deterrence (hysteresis) hypothesis for fraud, and sexual offences in the UK. Using panel unit root tests that allow for structural breaks they find evidence that supports a natural crime rate for all seven G7 countries (Canada, France, Germany, Italy, Japan, the UK, and the U.S.) over the period 1980–2006.

² Considering the utility of crime in this way is consistent with the economic model of choice whereby "... a person commits an offense if the expected utility to him exceeds the utility he could get by using his time and other resources at other activities." Becker (1968, p. 176).

Cook and Cook (2011) apply unit root tests that allow for structural breaks to the natural logarithms of the following annual U.S. crime rates over the period 1960–2007: aggravated assault, burglary, larceny, murder, motor vehicle theft, property crime (which is the sum of burglary, larceny and motor vehicle theft), rape, robbery and violent crime (being the aggregate of aggravated assault, murder, rape and robbery). The unit root hypothesis is rejected for all crime rates considered, suggesting a natural rate for all categories.

For annual Indian data over the period 1953–2012, Sahu and Mohanty (2016) find (using unit root tests that allow for structural change) that there is a natural rate of crime for the total crime rate as well as the specific crimes of burglary, cheating, counterfeiting, criminal breach of trust, dacoity, kidnapping and abduction, other crimes, and theft. In contrast, they cannot reject the hysteresis hypothesis for murder, riots, and robbery. They conclude that their “... findings are consistent with the literature which argues that crimes with pecuniary motives are more likely to have natural rates.” Sahu and Mohanty (2016, p. 344).

Ohlan (2020) tests for a natural crime rate in India for various measures of crime using both aggregate country data (available annually from 1853, 1954 or 1971, depending upon the measure, to 2016) and regional state level data (available annually between 1988 and 2016). The motivation for considering the latter is the considerable variation in Indian crime rates across states. The measures analysed were all crimes, burglary, cheating, murder, rape, riot, robbery, and theft. Time-series unit root tests that allow structural breaks yielded the following conclusion. “The empirical analysis indicates that most of the regional crime rates series are stationary which implies the existence of natural rate of crime in India. Based on our findings it is suggested that India should focus on improving the socioeconomic status of the general masses instead of devoting more resources to short-term measures of reducing crime rates.” (Ohlan 2020, p. 93).

Uzuner et al. (2024) apply panel unit root and stationarity tests that accommodate both structural breaks and cross-sectional dependence to 10 emerging economies’ country level incarceration rates (to proxy crime rates) annually over the period 2003–2017. The countries in the panel are Brazil, Bulgaria, Chile, Colombia, Czech Republic, Greece, Hungary, Peru, Poland and Turkey. They conclude that their results support the existence of a natural rate of crime for the panel of countries they consider.

In summary, the use of persistence testing methods that allow for structural breaks often (though not always) suggest support for evolving natural crime rates using both aggregate and disaggregated measures in various countries (including the U.S.). While the literature has tested for a natural rate of various crime rate measures for different Indian regions no such tests have been conducted for the hate crime measure or for individual U.S. states. These are gaps in the literature that this paper intends to fill.

Medoff (1999) empirically tests a theoretical model of hateful behaviour based on utility maximisation using cross-sectional data for U.S. states in 1995. “Hate crimes are positively related to the unemployment rate, percentage of the population between ages 15 and 19 years, the extent of a state’s liberal ideology, and the educational level. Hate crimes are negatively related to the market wage rate. Law enforcement efforts and religious belief did not have a statistically significant impact

on hateful activity.” Medoff (1999, p. 970). Implications that arise from these results include the following. “First, as real wages increase over time, hateful activity should decrease as individuals shift towards less time-intensive forms of consumption. Second, if the unemployment rate rises over time, the opportunity cost of time falls for many people, leading to more consumption of the time-intensive hateful activity. Third, law enforcement efforts and appeals to spiritual beliefs will have little effect on hateful activity.” Medoff (1999, p. 970). If law enforcement expenditures have little effect on hateful behaviour a natural hate crime rate would be expected. Further, if real wages rise through time and cause a reduction in hateful behaviour this suggests (in combination with ineffective law enforcement spending) that the natural hate crime rate may be expected to decline through time, which may be approximated over a sample of data by a linear trend.³ We will therefore test whether hate crime rates are being continuously forced towards a linear trend (an evolving natural rate) as well as a constant mean.

According to Solarin et al. (2024), a series will likely exhibit the time-series properties of the series that it is determined by. Hence, the hate crime rate will be mean and/or trend reverting if its determinants are mean and/or trend reverting whereas if the determinants are unit root processes the hate crime rate will also likely be a unit root process. This implies that if the U.S. hate crime rate is determined by measures of economic hardship such as unemployment and the market wage rate the hate crime rate may be expected to have similar time-series properties to unemployment and/or the market wage rate.⁴

Omay et al. (2021) reject a unit root in the unemployment rate of all 23 OECD countries that they consider (including the U.S.). Rather they find unemployment rates tend towards an evolving natural rate (around structural breaks). Their unambiguous results contrast with the previous literature that they suggest provide inconclusive and mixed results on whether unemployment rates exhibit hysteresis or tend to a natural rate. If the unemployment rate determines the hate crime rate, the mixed evidence on the persistence of the former suggests the latter could be a unit root, mean reverting or trend reverting process for any particular U.S. state. This provides a motivation for testing the degree of persistence of U.S. states’ hate crime rates allowing for trends.

Research on the determinants of hate crime include the following. Using 2002 and 2008 data for U.S. states Ryan and Leeson (2011) find little evidence that hate groups are related to hate crime. However, their results indicate that economic hardship causes hate crime. Basu (2021) examined the determinants of hate crimes in India for the period 2009–2018 and found that politics based on majority rule exacerbates the frequency of hate crimes in this country. Cikara et al. (2022) examined the relationship between the size of minorities on the incidence of hate crime in the U.S. and the UK during 1990–2010. They conclude that the number of hate crimes rise as the size

³ Gil-Alana et al. (2023) present evidence (based on fractional integration methods) that U.S. real per-capita GDP has a unit root using annual data between 1890 and 2019. This is consistent with rising real incomes expected in a growing economy such as the U.S.

⁴ This may not always be the case, for example, if the hate crime rate is determined by two $I(1)$ series that cointegrate, the hate crime rate is effectively determined by an $I(0)$ linear combination and would therefore be expected to be $I(0)$ and not $I(1)$.

of a particular set of minority groups (relative to other minority groups) increases. The authors suggest that this supports the group reference dependence hypothesis, which states that majority groups are sensitive to the relative size of minority groups. Bhai Patel et al. (2024) considered the determinants of hate crime in India for the period 2018–2020. They find that a substantial share of hate crime is caused by hate speech, rumours, and false information diffused through social media platforms.

There are also studies on the economic and social impact of hate crime. Mellgren et al. (2021) assessed the consequence of hate crimes in Sweden during 2013 and concluded that, in certain cases, hate crimes hurt the victims more than non-hate crimes. Sullivan et al. (2016) found, for Australia, that hate crime may bolster racial prejudices if perpetrators are treated leniently and not harshly punished. Petach and Rumbaugh (2024) examined the effect of hate crimes by white perpetrators on the educational attainment of white and black people using U.S. data for the period 1990–2017. The results suggest that hate crimes by white perpetrators adversely affects the educational attainment of black people while having no such detrimental effect on the educational attainment of white people.

Other issues investigated in the literature include the measurement of hate crime, hate crime reporting, and the legal framework for hate crimes. Vergani et al. (2024) examined the measurement of hate crime, hate speech, and hate incidents and find that the quality of methodological and reporting standards of hate crimes need to be enhanced. Stacey (2015) argues that a more encompassing definition of hate crimes would raise the number of hate crime cases reported in the U.S. Mills et al. (2024) highlight the inconsistent reporting of hate crimes across U.S. states, and we discuss this issue in more detail below. Farrell and Lockwood (2023) suggest that the anti-hate crime movement in the U.S. successfully facilitated legal change resulting in the introduction of several hate crime laws.

The foregoing empirical literature suggests that several aspects of hate crime have been examined for different countries (including the U.S.) and that various measures of crime rates in countries as a whole have been tested for the existence of a natural rate. However, we are not aware of any previous empirical analysis of the persistence of hate crime for individual U.S. states nor of the application of fractional integration methods to test for a natural rate of hate crime. As far as we know, we are the first to test for persistence in hate crime rates for individual U.S. states using fractional integration methods.

3 Methodology

The econometric methodology used to determine the persistence of U.S. hate crime rates is based on the concept of fractional integration. The order of integration is the number of times (d) a series must be differenced to render it stationary (denoted $I(d)$), where d may be a fractional value. Assuming that $\{u(t), t=0, \pm 1, \dots\}$ is a covariance stationary ($I(0)$) process (with zero mean, constant variance and zero covariances), we say that $\{x(t), t=0, \pm 1, \dots\}$ is integrated of order d (denoted $I(d)$) if it can be expressed as:

$$(1 - L)^d x(t) = u(t), \quad t = 1, 2, 3, \dots \quad (1)$$

where L is the lag operator, such that, $Lx(t) = x(t-1)$ and d may be any real number.

For non-integer d , the polynomial on the left-hand side of (1) can be expanded as:

$$\sum_{j=0}^{\infty} \binom{d}{j} (-1)^j L^j = 1 - dL + \frac{d(d-1)}{2} L^2 - \dots$$

Hence, $x(t)$ can be expressed as:

$$x(t) = dx(t-1) - \frac{d(d-1)}{2} x(t-2) + \dots + u(t).$$

In this context, d indicates the degree of persistence of the series where a higher value of d indicates a higher degree of dependence between the observations.

This specification allows us to consider a wide range of processes based on fractional values of d , including the following:

- (i) Anti-persistence process ($d < 0$),
- (ii) Short memory process ($d = 0$),
- (iii) Long memory covariance stationary process ($0 < d < 0.5$),
- (v) Nonstationary mean reverting process ($0.5 \leq d < 1$),
- (vi) Nonstationary unit root process ($d = 1$),
- (vii) Explosive process ($d > 1$).

In our empirical application we additionally allow a potential deterministic linear trend of the following form to permit the possibility of a trend reverting process:

$$y(t) = \alpha + \beta t + x(t), \quad t = 1, 2, 3, \dots \quad (2)$$

where $y(t)$ is the observed data, and α and β are unknown parameters on the constant and linear time trend, respectively. Thus, the model we consider is given by (1) and (2), which may be compactly written as:

$$y(t) = \alpha + \beta t + x(t), \quad (1 - L)^d x(t) = u(t). \quad (3)$$

If the coefficient on the trend term is significant the above interpretations for the different values of d should refer to whether the process reverts to a trend rather than the mean (under the alternative hypothesis).

The parameters in (3) are estimated by maximum likelihood in the frequency domain using a simple version of the testing approach proposed in Robinson (1994), which is widely used in empirical applications.

4 Data

Because data is missing in 15 U.S. states, we use the available hate crime data in the 36 remaining states for the period 1993–2022 (which is a longer time-series sample than the only other unit root analysis by region of natural crime rates, which was by Ohlan 2020; for India). The hate crime rate data that we use is defined as the number of hate crimes per 100,000 people and the number of hate crimes is obtained from the *Crime Data Explorer* of the Federal Bureau of Investigation (CDEFBI). The population series is from the U.S. Bureau of Economic Analysis' *Regional Data Explorer*. While the hate crime data are available from 1991 in CDEFBI, there are missing observations in 1991 and 1992 for many states. Hence, our sample period starts in 1993. Descriptive statistics for U.S. hate crime rates are given in Table 1. The District of Columbia (9.694) and New Jersey (8.024) are the states with by far the highest mean hate crime rates. In contrast, the states of Florida (0.983), Georgia (0.578) and Louisiana (0.560) have the lowest mean hate crime rates. For 15 states' hate crime rates there is evidence of non-normal distributions according to the Jarque-Bera test.

Figures 1 and 2 display the hate crime rates for each state. These rates either fluctuate around a constant (above zero) mean or around a trend. This justifies our consideration of econometric specifications of (3) that, first, solely include an intercept and, second, have both a constant and linear trend. We also consider (3) that excludes both an intercept and trend to accommodate a state's hate crime rate that is non-trended and not significantly greater than zero. The graphs demonstrate that hate crime rates exceed zero for every year for all U.S. states (as would be expected). Hate crime rates appear to systematically decline over the time period considered for Delaware, Florida, Idaho, Illinois, Maryland and Rhode Island. Conversely, hate crime rates exhibit a general rise over the sample for the District of Columbia, Georgia, Iowa, Kentucky, Louisiana, North Carolina, North Dakota, Ohio and Vermont. The extent to which these states exhibit reversion towards significant deterministic linear trends will be revealed by our fractional integration tests. Nevertheless, the graphs illustrate heterogeneity in hate crime rate time paths across U.S. states over the 1993–2022 sample period which justifies our testing for a natural rate for each individual state.

5 Empirical results

Table 2 displays the estimates of d obtained from (3) for each of the 36 U.S. states under the following three standard specifications of deterministic terms: (i) no deterministic terms; (ii) only a constant; and (iii) a constant and linear time trend. The estimation results for d are qualitatively similar across the three deterministic specifications for each state, nevertheless we highlight the statistics of the favoured specification for each U.S. state in bold. The preferred deterministic specification is selected based on the significance of the deterministic terms. That is, if the time trend has a statistically significant coefficient at the 10% level, we favour the specification that includes both an intercept and trend. Whereas, if the time trend's coefficient is insignificant, we prefer the model with only a constant provided the intercept's coefficient

Table 1 Descriptive statistics for hate crime rates

State	Mean	Standard deviation	Maximum value	Minimum value	Jarque-Bera
California	3.716	1.519	6.480	1.121	1.463 (0.481)
Colorado	3.112	1.120	5.410	1.303	1.151 (0.563)
Connecticut	3.507	0.898	5.601	2.024	0.647 (0.724)
Delaware	3.504	2.242	8.978	0.889	2.963 (0.227)
District of Columbia	9.694	8.907	32.195	0.342	6.992** (0.030)
Florida	0.983	0.437	1.828	0.324	2.318 (0.314)
Georgia	0.578	0.576	2.230	0.114	24.500*** (0.000)
Idaho	2.915	1.911	9.578	1.154	36.172*** (0.000)
Illinois	1.489	1.130	2.866	0.479	127.836*** (0.000)
Indiana	1.252	0.573	2.661	0.550	3.197 (0.202)
Iowa	1.060	0.715	3.501	0.192	18.756*** (0.000)
Kentucky	2.783	1.724	8.520	0.103	12.544*** (0.002)
Louisiana	0.560	0.566	2.691	0.087	52.011*** (0.000)
Maine	3.690	1.573	6.051	0.563	1.703 (0.427)
Maryland	3.138	2.347	7.518	0.268	2.259 (0.323)
Michigan	4.336	1.062	6.400	2.592	1.340 (0.512)
Missouri	1.903	0.667	3.337	0.960	2.733 (0.255)
Nevada	2.746	1.274	5.238	0.167	0.589 (0.745)
New Jersey	8.024	2.837	15.403	3.187	1.588 (0.452)
New Mexico	1.156	0.746	3.357	0.096	7.522** (0.023)
New York	3.42	0.838	4.927	2.015	2.333 (0.311)
North Carolina	1.143	0.699	2.88	0.096	4.620* (0.099)
North Dakota	2.265	1.777	6.977	0.156	5.219* (0.073)
Ohio	2.844	0.740	4.485	1.665	2.387 (0.303)
Oklahoma	1.249	0.469	2.473	0.547	3.195 (0.202)
Oregon	4.011	1.710	6.869	1.329	1.234 (0.540)
Pennsylvania	1.034	0.792	2.671	0.149	7.965** (0.019)
Rhode Island	2.74	1.567	5.935	0.473	1.892 (0.388)
South Carolina	1.645	0.680	3.378	0.601	1.207 (0.547)
South Dakota	2.521	2.281	11.177	0.136	52.806*** (0.000)
Tennessee	2.292	1.201	4.956	0.039	0.301 (0.860)
Texas	1.261	0.514	2.027	0.531	1.746 (0.418)
Utah	2.429	0.929	5.242	1.017	11.423*** (0.003)
Vermont	3.591	2.392	10.852	0.172	8.615** (0.013)
Virginia	2.482	1.167	4.929	0.760	3.399 (0.182)
Washington	4.489	1.594	7.600	2.708	4.651* (0.09)

***, **, * denote significance at the 1%, 5%, 10% levels. Probability values are in parentheses

is significant. If the intercept's coefficient is not significant, we favour the specification with no deterministic terms.

For three states (California, North Dakota and Tennessee) the specification with no deterministic terms is preferred. For 20 states, the model including only an intercept is favoured, while the specification containing both intercept and trend is selected for the remaining 13 states.

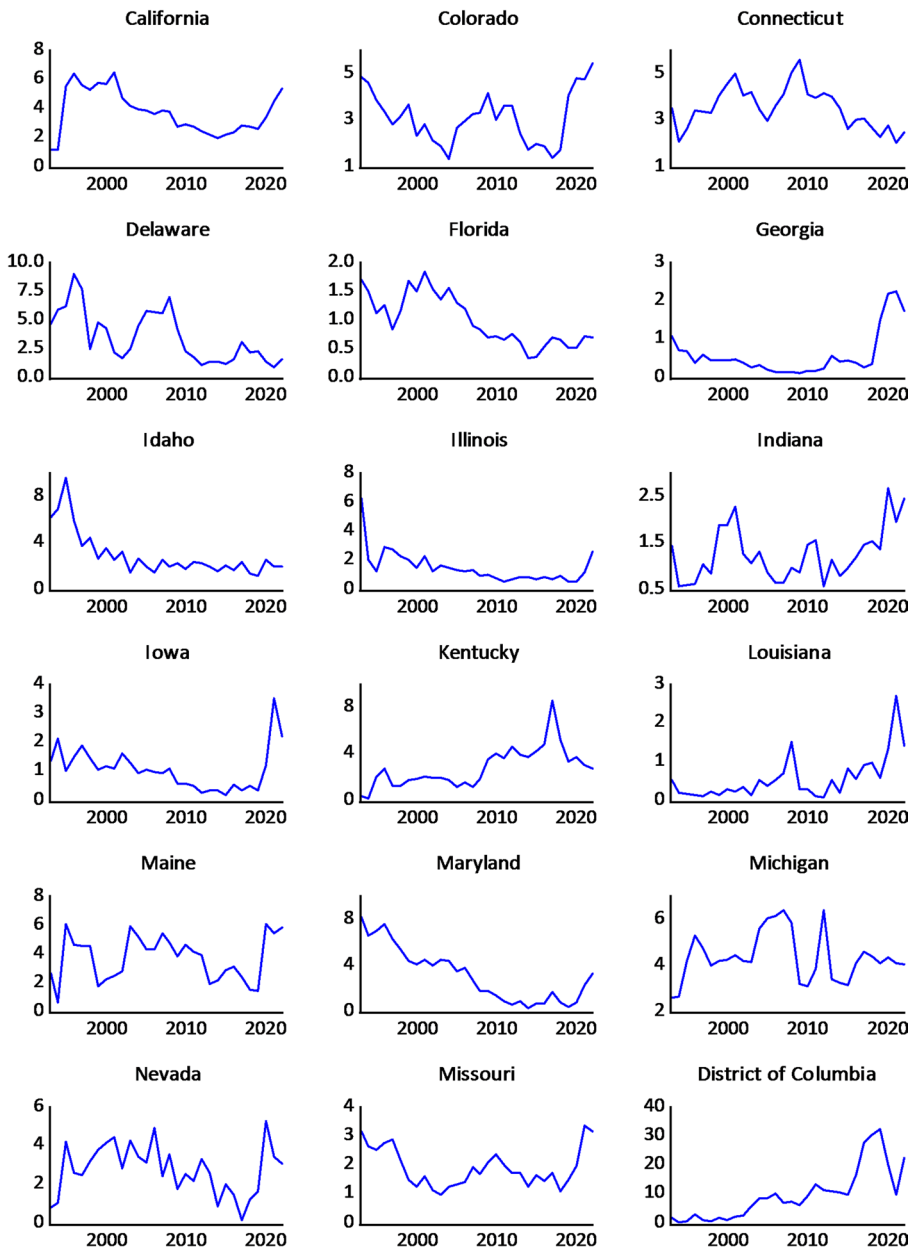


Fig. 1 Trend of hate crime in 18 U.S. states

Table 3 reports the estimated coefficients (and associated t-statistics) for the deterministic terms as well as the estimated order of integration parameter, d (with the corresponding confidence intervals) for the favoured specifications. Six of the 13 states where the favoured specification includes both intercept and trend have a positive trend. Provided $d < 1$ this implies that any evident stochastic process revolves

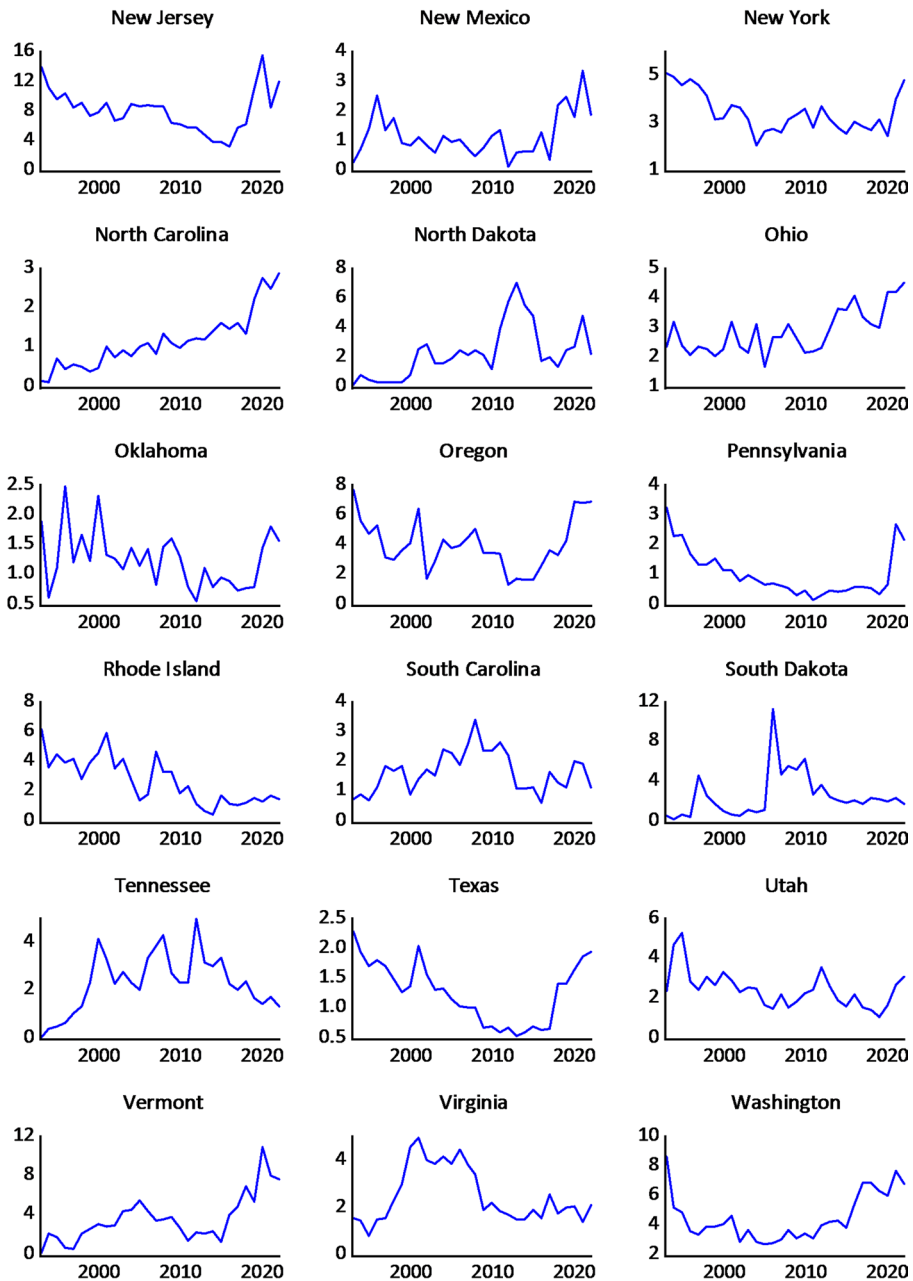


Fig. 2 Trend of hate crime in another 18 U.S. states

around a continuous rise in the hate crime rate over the sample. These 6 states are the District of Columbia, which has the largest trend coefficient (0.74), and, in descending order of trend coefficient size, Vermont (0.23), Kentucky (0.12), North Carolina (0.08), Ohio (0.06) and Louisiana (0.04). All 6 states were identified as exhibiting

Table 2 Estimates of the differencing parameter, d

State	No terms	An intercept	A linear time trend
California	1.15 (0.92, 1.48)	1.10 (0.53, 1.48)	1.10 (0.79, 1.44)
Colorado	0.94 (0.68, 1.31)	0.93 (0.65, 1.28)	0.93 (0.65, 1.28)
District of Columbia	0.67 (0.43, 1.62)	0.70 (0.48, 1.65)	0.57 (-0.04, 1.64)
Connecticut	0.73 (0.49, 1.05)	0.74 (0.50, 1.18)	0.73 (0.48, 1.19)
Delaware	0.88 (0.56, 1.37)	0.67 (0.38, 1.22)	0.57 (0.04, 1.22)
Florida	0.79 (0.58, 1.11)	0.70 (0.51, 1.10)	0.68 (0.38, 1.10)
Georgia	0.89 (0.70, 1.19)	1.19 (0.83, 2.13)	1.19 (0.80, 2.14)
Idaho	0.53 (0.53, 1.16)	0.56 (0.39, 0.84)	0.56 (0.36, 0.84)
Illinois	0.46 (0.20, 0.85)	0.33 (0.14, 1.24)	0.34 (0.02, 1.21)
Indiana	0.53 (0.23, 0.84)	0.48 (0.17, 0.82)	0.47 (0.20, 0.81)
Iowa	0.75 (0.54, 1.00)	0.61 (0.38, 0.93)	0.62 (0.37, 0.93)
Kentucky	0.53 (0.30, 0.99)	0.60 (0.40, 0.99)	0.51 (0.08, 0.99)
Louisiana	0.40 (0.18, 0.67)	0.44 (0.20, 0.73)	0.31 (0.20, 0.65)
Maine	0.54 (0.16, 0.97)	0.20 (-0.19, 0.86)	0.31 (-0.21, 0.83)
Maryland	0.97 (0.75, 1.28)	0.96 (0.73, 1.35)	0.95 (0.69, 1.33)
Michigan	0.74 (0.39, 1.16)	0.43 (0.07, 1.09)	0.48 (0.09, 1.08)
Missouri	0.89 (0.67, 1.18)	0.92 (0.65, 1.29)	0.92 (0.65, 1.29)
North Carolina	0.57 (0.38, 0.84)	0.55 (0.37, 0.80)	0.50 (0.23, 0.82)
North Dakota	0.72 (0.35, 1.34)	0.75 (0.44, 1.33)	0.73 (0.30, 1.33)
Nevada	0.48 (0.19, 0.77)	0.27 (0.04, 0.66)	0.28 (-0.08, 0.70)
New Jersey	0.75 (0.52, 1.10)	0.67 (0.44, 0.99)	0.68 (0.44, 0.99)
New Mexico	0.46 (0.20, 0.74)	0.37 (0.10, 0.71)	0.40 (0.17, 0.71)
New York	0.99 (0.72, 1.35)	0.76 (0.52, 1.12)	0.75 (0.49, 1.12)
Ohio	0.67 (0.31, 0.11)	0.44 (0.25, 0.72)	0.33 (0.06, 0.71)
Oklahoma	0.40 (0.07, 0.68)	0.15 (-0.03, 0.43)	-0.07 (-0.56, 0.39)
Oregon	0.69 (0.47, 0.99)	0.67 (0.42, 1.02)	0.68 (0.42, 1.02)
Pennsylvania	0.80 (0.60, 1.05)	0.83 (0.59, 1.17)	0.85 (0.63, 1.16)
Rhode Island	0.58 (0.37, 0.86)	0.42 (0.27, 0.64)	0.13 (-0.34, 0.67)
South Carolina	0.61 (0.36, 0.92)	0.60 (0.36, 0.95)	0.61 (0.38, 0.95)
South Dakota	0.30 (0.09, 0.62)	0.32 (0.11, 0.63)	0.32 (0.10, 0.63)
Tennessee	0.64 (0.39, 0.99)	0.65 (0.42, 0.99)	0.67 (0.45, 0.99)
Texas	0.90 (0.70, 1.18)	0.96 (0.76, 1.26)	0.97 (0.76, 1.25)
Utah	1.08 (0.70, 1.63)	0.51 (0.23, 1.38)	0.30 (-0.15, 1.40)
Vermont	0.61 (0.38, 0.89)	0.60 (0.36, 0.88)	0.60 (0.37, 0.88)
Virginia	0.99 (0.78, 1.31)	0.96 (0.74, 1.27)	0.96 (0.75, 1.27)
Washington	0.55 (0.37, 0.83)	0.91 (0.57, 1.40)	0.93 (0.58, 1.34)

The values in brackets are confidence intervals. Bold emphasis highlights the statistics for the favoured deterministic specification for each state

general increases over the sample from our visual inspection of the graphs. However, the 3 states (Georgia, Iowa and North Dakota) where graphical analysis suggested a general upward tendency in hate crime rates do not have statistically significant upward deterministic trends. On the other hand, there are seven states (Idaho, Delaware, Rhode Island, Illinois, Utah, Florida and Oklahoma) where the coefficient on the trend is negative, indicating a general fall in the hate crime rate over the period under study. Idaho's trend coefficient (-0.17) is the largest in magnitude of these 7 states whereas Oklahoma's trend coefficient (-0.02) is the smallest in absolute value.

Table 3 Estimates of the favoured deterministic specifications used for inference

State	Estimated d	Intercept	Trend
California	1.15 (0.92, 1.48)	—	—
Colorado	0.93 (0.65, 1.28)	4.7840 (6.28)	—
District of Columbia	0.57 (−0.04, 1.64)	−0.7098 (−0.17)	0.7424 (2.80)
Connecticut	0.74 (0.50, 1.18)	3.3102 (5.69)	—
Delaware	0.57 (0.04, 1.22)	5.5798 (4.20)	−0.1464 (−1.67)
Florida	0.68 (0.38, 1.10)	1.6363 (8.05)	−0.0354 (−2.19)
Georgia	1.19 (0.83, 2.13)	1.1267 (4.04)	—
Idaho	0.56 (0.36, 0.84)	6.2789 (6.63)	−0.1694 (−2.74)
Illinois	0.34 (0.02, 1.21)	3.3006 (5.37)	−0.0906 (−2.69)
Indiana	0.48 (0.17, 0.82)	1.2554 (4.05)	—
Iowa	0.61 (0.38, 0.93)	1.4098 (2.94)	—
Kentucky	0.51 (0.08, 0.99)	0.6263 (1.66)	0.1166 (2.02)
Louisiana	0.31 (0.20, 0.65)	0.0297 (2.10)	0.0399 (2.64)
Maine	0.20 (−0.19, 0.86)	3.6092 (5.41)	—
Maryland	0.96 (0.73, 1.35)	7.9923 (10.96)	—
Michigan	0.43 (0.07, 1.09)	3.7579 (5.89)	—
Missouri	0.92 (0.65, 1.29)	3.0904 (7.02)	—
North Carolina	0.50 (0.23, 0.82)	0.0236 (2.10)	0.0796 (6.02)
North Dakota	0.72 (0.35, 1.34)	—	—
Nevada	0.27 (0.04, 0.66)	2.6142 (5.36)	—
New Jersey	0.67 (0.44, 0.99)	11.8839 (6.34)	—
New Mexico	0.37 (0.10, 0.71)	1.0857 (2.98)	—
New York	0.76 (0.52, 1.12)	4.8083 (9.10)	—
Ohio	0.33 (0.06, 0.71)	2.0819 (6.01)	0.0572 (3.02)
Oklahoma	−0.07 (−0.56, 0.39)	1.5242 (10.76)	−0.0181 (−2.22)
Oregon	0.67 (0.42, 1.02)	6.3824 (5.37)	—
Pennsylvania	0.83 (0.59, 1.17)	2.9780 (6.54)	—
Rhode Island	0.13 (−0.34, 0.67)	4.9334 (10.91)	−0.1396 (−5.66)
South Carolina	0.60 (0.36, 0.95)	1.0763 (2.48)	—
South Dakota	0.32 (0.11, 0.63)	0.00001 (1.64)	—
Tennessee	0.64 (0.39, 0.99)	—	—
Texas	0.96 (0.76, 1.26)	2.2558 (8.95)	—
Utah	0.30 (−0.15, 1.40)	3.2486 (6.65)	−0.0477 (−1.80)
Vermont	0.60 (0.37, 0.88)	0.3069 (2.24)	0.2276 (2.60)
Virginia	0.96 (0.74, 1.27)	1.5334 (2.43)	—
Washington	0.91 (0.57, 1.40)	8.2861 (8.49)	—

The estimated value of d is given in the column headed “Estimated d ”. Coefficients and corresponding t -statistics (in parentheses) for the deterministic terms are given in the columns headed “Intercept” and “Trend”

Most of these 7 states were identified as exhibiting downward trends in the above graphical analysis. Discrepancies between the trends identified by a significant coefficient on the deterministic trend in the favoured specification and those indicated by visual inspection of the graphs should be accounted for by the degree of persistence in hate crime rates.

We now discuss the estimated degree of persistence for each state with reference to the estimated fractional order of integration (differencing) parameter, d , reported

in Table 3. Firstly, the confidence intervals of the differencing parameter are wide, which is due to the relatively limited number of observations available for each state. Secondly, the results are highly heterogeneous across states. No state exhibits anti-persistence ($d < 0$). Short memory processes ($d = 0$) in the hate crime rate are evident for the following 5 states, District of Columbia, Oklahoma, Rhode Island, Maine and Utah (because the lower boundary of the confidence interval is below 0). Three of these (Oklahoma, Rhode Island and Utah) are $I(0)$ processes around a downward linear trend whereas the District of Columbia's (Maine's) hate crime rate is $I(0)$ around a positive trend (constant mean). However, the very wide confidence intervals for the District of Columbia and Utah suggests that both the $d = 0$ and $d = 1$ null hypotheses cannot be rejected. Hence, the District of Columbia's hate crime rate could be $I(0)$ around a rising linear trend or $I(1)$ and Utah's hate crime rate could be $I(0)$ around a declining linear trend or $I(1)$.

For 14 states $0 < d < 1$ because the confidence intervals only include values of d greater than 0 and below 1. This indicates that the hate crime rate series for these states exhibit mean/trend reversion either because they are long memory covariance stationary processes ($0 < d < 0.5$) or because they are nonstationary mean/trend reverting processes ($0.5 \leq d < 1$). These states are Idaho ($d = 0.56$), Indiana (0.48), Iowa (0.61), Kentucky (0.51), Louisiana (0.31), North Carolina (0.50), Nevada (0.27), New Jersey (0.67), New Mexico (0.37), Ohio (0.33), South Carolina (0.60), South Dakota (0.32), Tennessee (0.64) and Vermont (0.60). In all these states, shocks are expected to be transitory, with the effects disappearing faster for lower values of d . For the following states the hate crime rate exhibits reversion towards a (generally non-zero) constant mean: Indiana, Iowa, Nevada, New Jersey, New Mexico, South Carolina, South Dakota and Tennessee (zero mean). Reversion towards a downward trend is evident for Idaho. Whereas the series displays reversion towards an upward trend for Kentucky, Louisiana, North Carolina, Ohio and Vermont.

For the remaining 17 states mean/trend reversion in the hate crime rate is unambiguously rejected because either the null hypothesis that $d = 1$ (indicating a unit root process) cannot be rejected (the upper bound of the confidence interval exceeds 1) or (for California and Georgia) the estimated value of d is greater than 1 (indicating a potentially explosive process).⁵

We now consider whether the heterogeneity of our inference across states is related to differences in reporting practices of hate crime statistics across states. Mills et al. (2024) suggest that the 1990 U.S. Hate Crime Statistics Act (HCSA) has led to differences in the degree of reporting of hate crime statistics by different police agencies. This is because the HCSA only requires governments to report hate crime statistics at federal and state level, it does not require law enforcement agencies to report statistics. This uniquely U.S. phenomenon led the authors to identify three categories of local U.S. hate crime statistics reporting, being: true compliance (reporting hate crime statistics regularly or occasionally); non-compliance (failure to report hate crime statistics at all); and ceremonial compliance (being the consistent reporting of non-varying zero hate crimes that is unlikely to reflect the truth). Mills et al.'s (2024,

⁵ For 3 of these 17 states (Delaware, Florida and Illinois) the hate crime rate is $I(1)$ rather gravitating towards a downward trend.

p. 392) data shows that only 24% of police agencies exhibit true compliance. Using cross-sectional data summarized across years and by county, their findings include the following. True compliance is more likely in counties with a higher Republican vote share; true compliance is significantly less likely than ceremonious compliance by agencies in the Confederate South; and noncompliance is more likely than ceremonious compliance in counties with a greater history of racial terror lynchings. The inconsistent reporting of hate crime statistics across different U.S. regions is therefore attributed to factors including political and historical contexts as well as resources. They suggest "... that even if hate crime statistics are considered to be unreliable indicators of true hate crime offending, they can still be interpreted as reliable indicators of societal responses to hate crime behavior." Mills et al. (2024, p. 383).

In their empirical analysis of the role of political threat and emboldenment on violent hate crime statistics, Dugan and Chenoweth (2020) suggest applying robustness checks using data from agencies with high compliance (meaning the consistent reporting of hate crime statistics by police agencies). We take on board this notion and apply a robustness check by considering whether heterogeneity of inference displayed in the full sample of 36 U.S. states is consistent with that obtained from a sub-sample that excludes data on states with the least reliable hate crime data. To do this, we follow Mills et al. (2024) in using the Brennan Center for Justice's table of state hate crime statutes to determine which states mandate data collection (<https://www.brennancenter.org/our-work/research-reports/state-hate-crimes-statutes>). This source shows that three states included in our sample (Indiana, North Dakota, South Carolina) are regarded as not having any genuine hate crime laws. We therefore treat our results for these states with caution and exclude them from consideration in our robustness check sub-sample. There are a further 9 states that, while they have hate crime laws, they do not require data collection on hate crimes (Colorado, Delaware, Georgia, Missouri, Nevada, Ohio, South Dakota, Tennessee, and Vermont). The data for these states are regarded to be subject to the greatest inaccuracy and are also excluded from our sub-sample. If we remove these 12 states, we find the following conclusions for the remaining 24 U.S. states. For 10 states there is a natural hate crime (6 exhibit trend reversion), for 12 states there is no reversion to a natural hate crime rate and for two states the results are ambiguous. Removing the states where the data is regarded as most questionable, the proportions of states with mean reversion, trend reversion and hysteresis are similar to the full-sample. Hence, our conclusion of heterogeneity of inference across states remains.

Dugan and Chenoweth (2020, p. 729) suggest that the "... states with the highest average number of participating years per agency are Texas (17.2), Iowa (16.2), and New York (15.9), whereas agencies in Hawaii (0), Alaska (.47), and Georgia (1.95) have the lowest participation" – where participation means submitting reports of hate crime. These observations are consistent with the information in the Brennan Center for Justice's table on the number of hate laws and whether data collection is required for each state. This suggests that Texas, Iowa and New York are probably the states with the most reliable hate crime data. Our results suggest that Iowa has a natural hate crime rate whereas Iowa and New York exhibit hysteresis. Hence, there remains heterogeneity of inference across states with the data that is most likely to be reli-

able. While there may be unreliability of data across states, our robustness checks suggest our inference for the 36 U.S. states under consideration is broadly robust to this variation.

In summary, our results suggest unambiguous evidence of hate crime hysteresis (unit roots) for 17 states (California, Colorado, Connecticut, Delaware, Florida, Georgia, Illinois, Maryland, Michigan, Missouri, New York, North Dakota, Oregon, Pennsylvania, Texas, Virginia, and Washington). This suggests that crime prevention spending to deter offending can be effective in the long run for these states. A natural hate crime rate (mean/trend reversion) is unambiguously evident for the following 17 states: Idaho, Indiana, Iowa, Kentucky, Louisiana, Maine, North Carolina, Nevada, New Jersey, New Mexico, Ohio, Oklahoma, Rhode Island, South Carolina, South Dakota, Tennessee and Vermont. For these states, law enforcement expenditures aimed at a crime prevention and deterrence will only be effective in the short run because hate crimes will return to their natural rate in the long run. Corrective policies that can lower the natural rate are recommended for these states. While hate crime rates in the District of Columbia and Utah may be trend reverting, they may also be $I(1)$ due to an ambiguity of inference for these states. The classification for each state is given in Table 4.

6 Conclusion and policy implications

The literature has previously considered whether there is a natural crime rate at the aggregate country level (only one paper for India performs a regional analysis), for property and other profit motivated crimes as well as a variety of crimes against people. The early empirical evidence based on unit root and stationarity tests provided broadly mixed results which depend on the country, econometric method used, and type of crime being considered. More recent testing, especially that which allows an evolving natural rate (for example, by accommodating potential structural breaks), has found more widespread (though not universal) support for crime rates tending towards a natural rate. A general conclusion is that crimes with a monetary motivation are more likely to have a natural crime rate than those involving violence.

However, we are not aware of any previous studies that test whether hate crime rates (which are not primarily motivated by money) tend towards a natural rate. Nor are we aware of any previous study that applies such tests to individual U.S. states while the use of fractional integration methods in this context is, at best, rare. Hence, we believe we are the first to test whether there is a natural rate of hate crime in each of 36 U.S. states using fractional integration methods. For 17 states there is evidence of a natural hate crime rate. For 9 states the hate crime rate exhibits mean reversion without a trend (Indiana, Iowa, Maine, Nevada, New Jersey, New Mexico, South Carolina, South Dakota and Tennessee), which is consistent with a constant natural hate crime rate. The hate crime rate tends to a positive trend for 5 states (Kentucky, Louisiana, North Carolina, Ohio and Vermont) and for 3 states there is unambiguous evidence that the hate crime rate exhibits reversion to a downward trend (Idaho, Oklahoma and Rhode Island). For these last 8 states this is consistent with an evolving natural rate over the sample. For the 17 states that have a natural hate crime rate,

Table 4 Process identified for each state (degree of integration and deterministic terms)

Short memory $I(0)$	$I(d)$ with $0 < d < 1$	Unit roots or $I(1)$
Mean reversion (intercept only)	Mean reversion (no deterministic terms)	Unit roots with $d = 1$
Maine (0.20)	Tennessee (0.64)	Colorado (0.93)
Negative trend reversion	Mean reversion (intercept only)	Connecticut (0.74)
Oklahoma (−0.07), [−0.0181]	Indiana (0.48)	Delaware (0.57)
Rhode Island (0.13), [−0.1396]	Iowa (0.61)	Florida (0.68)
Negative trend reversion or $I(1)$	Nevada (0.27)	Illinois (0.34)
Utah (0.30), [−0.0477]	New Jersey (0.67)	Maryland (0.96)
Positive trend reversion or $I(1)$	New Mexico (0.37)	Michigan (0.43)
District of Columbia (0.57), [0.7424]	South Carolina (0.60)	Missouri (0.92)
	South Dakota (0.32)	New York (0.76)
	Negative trend reversion	North Dakota (0.72)
	Idaho (0.56), [−0.1694]	Oregon (0.67)
	Positive trend reversion	Pennsylvania (0.83)
	Kentucky (0.51), [0.1166]	Texas (0.96)
	Louisiana (0.31), [0.0399]	Virginia (0.96)
	North Carolina (0.50), [0.0796]	Washington (0.91)
	Ohio (0.33), [0.0572]	Unit roots with $d > 1$
	Vermont (0.60), [0.2276]	California (1.15)
		Georgia (1.19)

States listed under the heading “Short memory $I(0)$ ” are identified when the lower confidence interval for d is no greater than zero. States listed under the heading “ $I(d)$ with $0 < d < 1$ ” are identified when the lower confidence interval for d exceeds 0 and the upper confidence interval for d is below 1. States listed under the heading “Unit roots or $I(1)$ ” are identified when the upper confidence interval for d is at least 1. The point estimate of d is given in round brackets. For states with hate crime rates that are not identified as $I(1)$, they are listed into categories according to the type of reversion. The sub-heading “Mean reversion (no deterministic terms)” indicates a process that tends towards a zero mean. The sub-heading “Mean reversion (intercept only)” indicates a process that tends towards a non-zero mean. The sub-heading “Negative trend reversion” indicates a process that varies around a downward sloping trend. The sub-heading “Positive trend reversion” indicates a process that fluctuates around an upward sloping trend. The sub-heading “Negative trend reversion or $I(1)$ ” indicates a process that varies around a downward sloping trend or is $I(1)$. “Positive trend reversion or $I(1)$ ” indicates a process that varies around an upward sloping trend or is $I(1)$.

spending on crime prevention measures to deter potential perpetrators will only be able to reduce offending in the short run because hate crimes will return to their natural rate in the long run. The focus should be on policies that can be effective in the long run by correcting the behaviour of potential offenders and thereby reduce the natural rate of hate crime. Such policies include those aimed at educating potential offenders, rehabilitating convicted criminals as well as reducing poverty and income inequality. While such corrective policies may seem particularly necessary in the 5 states where the hate crime rate reverts to an upward trend it should be borne in mind that these positive trends may reflect increased hate crime reporting/compliance over time, which is an issue that has been previously highlighted by Dugan and Chenoweth (2020). For the 3 states where the hate crime rate tends to a negative trend such corrective policies may already be in place or it may be that the downward trend is a consequence of increasing market wages in these states (as predicted by Medoff 1999). However, Medoff’s (1999) conjecture that rising market wage rates may lead to falling crime rates cannot be relied upon for hate crime rates in all U.S. states, suggesting that active policy intervention is required.

The results for the District of Columbia and Utah are ambiguous and indicate that the hate crime rate reverts to a trend or is $I(1)$. Future work is recommended to determine whether there is a natural hate crime rate in these two states and thereby indicate whether crime prevention (deterrence) or crime correction (that change the natural rate) policies will be most effective in the long run in these states. Clarifying which policy tools will be effective is particularly important for the District of Columbia which has the highest mean hate crime rate of all states we consider.

For the remaining 17 states there is no natural hate crime rate because the data is unambiguously non mean/trend reverting. Law enforcement expenditure aimed at deterring hate crime can be effective in both the short run and long run in these states.

The highly heterogeneous results across states demonstrates a strength of our approach in applying tests to individual states. This heterogeneity and difference in policy conclusions for different states cannot be revealed by testing at the aggregate country level. This represents a notable contribution of our paper given that the past literature for the U.S. has only tested for a natural rate at country level. We recommend that future research on different countries' crime rates test the competing natural rate and hysteresis hypotheses at regional level and not only at country level.

Like the previous literature on testing for natural rates in crime (Narayan et al. 2010; Cook and Cook 2011; Sahu and Mohanty 2016; Ohlan 2020; Uzuner et al. 2024) and unemployment (Omay et al. 2021) we have found a natural hate crime rate that evolves (rather than being constant) for some states. In our paper this is because our testing method allows linear trend reversion. As longer time-series for state level data becomes available we recommend future research consider tests that allow other forms of evolving natural hate crime rates. For example, applying fractional integration tests that permit non-linear trends. As a reviewer points out, future research could also consider panel unit root techniques, tests that accommodate structural breaks and relating stochastic time paths of hate crimes to contextual variables such as law changes, political shifts and triggering events to give a more refined assessment. Future work combining state-level policy histories with quantitative analysis could also help disentangle data artifacts from substantive crime dynamics.

Author contributions SS proposed the original idea. He wrote the intro and the review along with conclusions. LAGA wrote the methodology and conducted the empirical results and interpretation. CS contributed to the review, interpreted the results and the conclusions of the paper.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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