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Deadly tensions: the enduring impact of ethnic and religious diversity on lethal violence in the United States 1945–2023

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Abstract
This study investigates the long-term relationship between ethnic and religious diversity, democratic performance, and lethal violence in the United States from 1945 to 2023. This study is particularly important in the context of the United States, where growing diversity shapes the nation's social and political dynamics. Lethal violence is defined as the combined total of suicides and homicides. Using the bound testing approach and the Autoregressive Distributed Lag (ARDL) model, the analysis reveals a significant positive association between increased ethnic and religious diversity and higher levels of lethal violence, with this relationship holding for both suicides and homicides. In contrast, stronger democratic performance is found to have a significant negative relationship with lethal violence. These findings suggest that while diversity may pose challenges to social cohesion, the strength of democratic institutions can play a crucial role in mitigating its potential for violence. The study highlights the critical importance of democratic governance in promoting social stability within increasingly diverse societies.

Keywords Ethnic diversity · Religious diversity · Democratic performance · Lethal violence

JEL Classification J15 · Z12 · D72 · K42 · H56

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Introduction

The United States has long been regarded as a nation of immigrants, a country built upon the ideals of diversity, inclusion, and the blending of cultures (Pineau & Waters, 2016). Its social fabric is characterized by a profound ethnic and religious diversity that has evolved significantly over time, reflecting global migration patterns, historical injustices, and the broader forces of globalization. From the colonial era to the present day, the U.S. has experienced continuous demographic transformations, with waves of migration contributing to the rich mosaic of ethnic and religious groups that shape the nation today (Dinnerstein, 2009; Portes & Rumbaut, 2024). Ethnic diversity in the U.S. can be traced back to the earliest days of the nation's formation, with Native American populations representing the indigenous ethnic groups of the continent. However, the U.S. became increasingly ethnically diverse following the arrival of European settlers, enslaved Africans, and immigrants from Latin America, Asia, and other parts of the world (Spickard et al., 2022). This diversity was further intensified during the 20th and 21 st centuries as U.S. immigration laws became more inclusive, allowing greater numbers of people from non-European countries to settle in the U.S. By the mid-20th century, the country had witnessed dramatic demographic shifts, with significant increases in the population of African Americans, Latinx communities, Asian Americans, and various other ethnic groups (Perez & Hirschman, 2009).

This study examines the impact of ethnic and religious fractionalization (the degree to which a population is divided into a large number of distinct groups) and polarization (the extent to which a population is split into two or a few large, opposing groups) on lethal violence, suicides, and homicides. Today, the U.S. is home to a broad spectrum of ethnic groups, with the 2020 Census revealing that nearly 40% of the U.S. population identifies as non-white. This includes a vast array of identities such as African Americans, Hispanic and Latinx populations, Asian Americans, Native Americans, and multiracial individuals (Lee & Bean, 2004; Perez & Hirschman, 2009). The rapid growth of minority populations, especially among Hispanic and Asian communities, is reshaping the cultural, political, and economic landscape of the U.S (Frey, 2018). This ethnic diversity, while a source of vibrancy and strength, has also led to challenges related to inequality, discrimination, and racial tensions, particularly in the context of historical injustices such as slavery, segregation, and the mistreatment of indigenous peoples. In addition to ethnic diversity, the United States is home to a rich and diverse religious landscape, shaped by its founding principles of religious freedom and tolerance (Wald & Calhoun-Brown, 2014). The country's religious diversity is partly due to its history as a haven for religious refugees, including early European settlers seeking freedom from religious persecution. Over time, this openness to different religious traditions has resulted in a multi-faith society that includes Christianity, Judaism, Islam, Buddhism, Hinduism, Sikhism, and various indigenous and new religious movements (Portes & Rumbaut, 2024).

According to Pew Research, by the early 21 st century, religious minorities such as Muslims, Hindus, and Buddhists have experienced rapid growth in the U.S., largely due to immigration from regions such as South Asia, the Middle East, and Southeast

Asia. The U.S. also has a significant Jewish population, as well as growing numbers of religiously unaffiliated individuals, known as nones (Straughn & Feld, 2010). Religious diversity in the U.S. reflects not only the breadth of beliefs but also the complexity of religious identity. For instance, African American religious traditions, often centered around Christian churches, have long played a pivotal role in shaping U.S. social and political life, especially in the context of the civil rights movement. Similarly, the growing Muslim population, which includes immigrants, African American Muslims, and converts, has brought new perspectives and contributed to debates about Islam's place in American society. Yet, religious diversity has also been a source of tension, with instances of religious intolerance and violence, particularly against minority faith groups, including anti-Muslim sentiments following 9/11 and the long-standing history of anti-Semitism (Perez & Hirschman, 2009; Straughn & Feld, 2010).

Figure 1 shows the comparative divisions of ethnic and religious groups across the United States highlighting the rapid increase in both ethnic and religious diversity. The table illustrates the growing ethnic and religious diversity in the U.S. from 1950 to 2022. Ethnic fractionalization (EF) and ethnic polarization (EP) increased from 0.231 to 0.547 and from 0.429 to 0.739, respectively, reflecting the rising demographic diversity driven by immigration and population changes, which have reshaped the distribution and composition of ethnic groups. Religious fractionalization (RF) and religious polarization (RP) also followed upward trends, rising from 0.509 to 0.761 and from 0.777 to 0.794, indicating greater religious diversity influenced by immigration and societal changes, along with ongoing complexities in interreligious dynamics. The data underscores a trend toward increasing diversity in both ethnic and religious dimensions, along with nuanced changes in group dis-

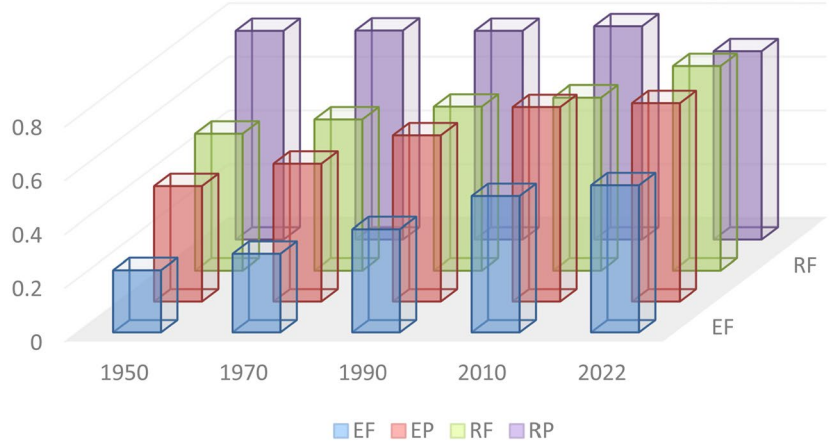

Fig. 1 Ethnic and religious diversity of the United States (Figure complied by the authors by updating and following the methodology of fractionalization index, and polarization index.). Source: Compiled by the author(s). Note: EF, EP, RF, and RP represent ethnic fractionalization, ethnic polarization, religious fractionalization, and religious polarization, respectively

tribution and interaction over time. While ethnic and religious diversity in the U.S. has fostered cultural exchange, innovation, and economic growth, it has also given rise to social and political tensions. These tensions are often tied to broader issues such as economic inequality, political polarization, and competition for resources. Historically, ethnic minorities in the U.S. have faced systemic discrimination, marginalization, and exclusion, which have perpetuated cycles of poverty, limited access to education and healthcare, and heightened experiences of social injustice (Beech et al., 2021). The legacy of slavery and segregation, coupled with contemporary racial inequalities, has made it difficult for many ethnic groups, particularly African Americans, to achieve full integration into American society.

Similarly, religious diversity has sometimes exacerbated cultural divides, particularly when religious groups have been viewed as outsiders or threats to the dominant cultural narrative. Anti-immigrant sentiment, often fueled by fear of the other, has manifested in discriminatory policies, hate crimes, and social exclusion. The rise of nationalist and nativist movements in recent decades has further complicated the conversation around ethnic and religious diversity, as some political actors and factions advocate for the preservation of a homogenous national identity, while others champion pluralism and inclusivity. In particular, ethnic and religious diversity have become flashpoints for debates about national identity, with questions about what it means to be "American" often framed in opposition to these minority groups. These tensions have occasionally erupted into violence, whether in the form of hate crimes, racial riots, or mass shootings and the rise in anti-Asian violence during the COVID-19 pandemic (Palmadessa, 2022).

Figure 2 reveals significant trends in suicide, homicide, and overall lethal violence rates in the United States from 1950 to 2020. Suicide rates gradually increased from 11.38 per 100,000 in 1950 to 13.89 in 2020, with notable peaks in the 2010 s, suggesting a steady rise in mental health challenges. Homicide rates peaked in the 1980 s and

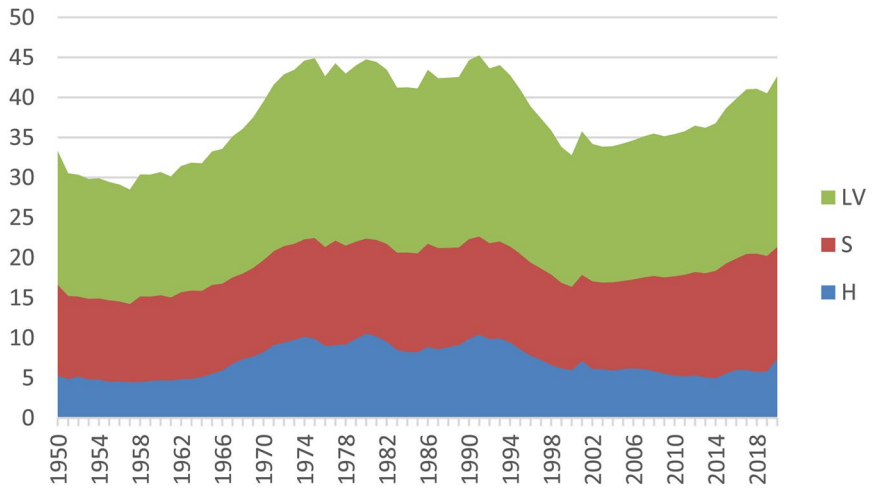

Fig. 2 Trends of growth rate of lethal violence, suicides and homicides of US

then declined, but spiked again in 2020, potentially due to the COVID-19 pandemic. The combined lethal violence rate increased from 16.65 in 1950 to 21.32 in 2020, reflecting the combined impact of suicide and homicide trends. The United States stands as a complex example of ethnic and religious diversity, where the richness of multiculturalism coexists with challenges stemming from historical and contemporary inequalities (Beech et al., 2021). While this diversity has contributed immensely to the nation's vibrancy and innovation, it has also underscored the critical need for effective governance, democratic performance, and social integration. Understanding how ethnic and religious diversity interact with broader political, economic, and social structures is crucial to addressing the root causes of violence and building a more inclusive, cohesive society (Amin, 2021; Amin & Ahmad, 2018; Novy et al., 2012).

The relationship between ethnic diversity, democratic performance, and lethal violence has drawn significant attention as diverse societies navigate challenges to social cohesion and stability. While ethnic diversity can foster cultural and economic growth, it also poses risks when democratic institutions fail to manage underlying tensions, potentially leading to unrest and violence. The United States, with its rich cultural mosaic, offers a valuable case for exploring these dynamics. Despite its democratic framework, the U.S. has faced episodes of violence rooted in ethnic and racial tensions. This study examines the interplay of ethnic diversity, democratic governance, and lethal violence in the U.S. from 1945 to 2023, analyzing indicators of ethnic composition, governance quality, and violence prevalence to understand their interconnected impacts.

This study follows the following sequence of chapters, in which the first chapter relates to introduction of study, the second chapter explores the literature review and chapter third consists of theoretical background of the study, data analysis and methodology, chapter four provides discussion of results. Finally, chapter five concludes the study and provides policy suggestion in the light of results.

Literature review and theoretical framework

Literature review

The relationship between ethnic diversity, democratic performance, and lethal violence is multifaceted and has been widely explored across political science, sociology, economics, and criminology. Some scholars argue that increasing ethnic diversity may lead to greater social fragmentation and violence, while others suggest that inclusive democratic governance can mitigate these risks and foster peace. This literature review synthesizes key interdisciplinary studies, focusing particularly on the U.S. context from 1945 to 2023.

A pivotal study by Ulmer and Harris (2013) highlights the role of religious contexts in mitigating violence among racial and ethnic groups in the United States. Using race-specific arrest data and religious congregation surveys, they found that religious institutions played a critical role in reducing violent crime, particularly for Black communities, by moderating the effects of disadvantage on violence. Similarly,

Leach (2014) examined cultural diversity in suicide risk, emphasizing the importance of ethnicity, religion, gender, and sexual orientation in shaping mental health outcomes. These findings underscore the need for culturally informed approaches to violence prevention.

Political and economic factors further influence lethal violence. Jacobs and Carmichael (2002) examined the political sociology of the death penalty, revealing that jurisdictions with larger minority populations are more likely to legalize capital punishment, with economic inequality and racial dynamics serving as key drivers. Similarly, Jacobs and van Spanje (2021) explored hate crimes in the Netherlands, finding that media portrayals and political rhetoric about immigration significantly influenced the rise of nonviolent hate crimes, illustrating the broader relevance of these dynamics. In the context of youth violence, Cook and Laub (2002) showed a significant decline in violent crime among U.S. youth since 1993, attributing this trend to changes in the crack cocaine trade rather than demographic or legal shifts. However, disparities in race, gender, and age persisted, reflecting the multifactorial nature of violence.

Research on Latin America by Rivera (2016) identified youth bulges, female workforce participation, and post-conflict states as key contributors to high homicide rates. Organized crime, particularly money laundering, was also linked to violence, emphasizing the need for stronger judicial systems and educational policies. Globally, Oberwittler (2019) demonstrated that poverty, inequality, and weak state legitimacy are strongly correlated with homicide rates. These findings highlight the importance of comprehensive social policies to reduce inequality and enhance governance.

Religious ideologies and community composition also play significant roles in shaping violence. Saiya and Manchanda (2024) found that Christian nationalist rhetoric increased violence against religious minorities in the U.S., demonstrating how political ideologies shape social violence. In contrast, studies like Awaworyi Churchill and Laryea (2019) show that higher ethnic and linguistic diversity can lower crime rates, challenging the assumption that diversity inherently leads to fragmentation. Amin and Ahmad (2018) found that both ethnic diversity and social exclusion significantly contribute to higher crime rates, especially property and violent crimes. Trawick and Howsen (2006) similarly noted that racial and ethnic homogeneity tends to reduce crime through greater social cohesion, adding complexity to the understanding of diversity and violence.

Lethal violence in the U.S. has often been tied to ethnic tensions, as seen in the civil rights struggles, race riots, and incidents of police violence. Collier and Hoeffler (2004) argue that ethnic polarization, political exclusion, and economic inequality create conditions conducive to violence. Crenshaw (2013) adds that systemic inequality and prejudice often result in violent uprisings, while Urbanik et al. (2020) highlight how political polarization along ethnic lines has exacerbated risks of lethal violence in recent years. Theoretical perspectives by Horowitz (1993) and Lijphart (2007) provide contrasting insights. Horowitz suggests that weak democratic institutions and political exclusion amplify violence, whereas Lijphart advocates for consociational democracy, where power-sharing among ethnic groups promotes stability.

Empirical studies in the U.S. context further illustrate these dynamics. Hanushek and Yilmaz (2022) found that regions with higher ethnic diversity and greater income

inequality experienced more frequent and violent ethnic conflicts. Acemoglu and Robinson (2013) demonstrated that economic exclusion of ethnic minorities has heightened tensions, particularly during the civil rights era. Studies on police violence and hate crimes, such as those by Gabbidon (2020), establish a clear relationship between ethnic tensions, political exclusion, and lethal violence.

The literature reveals that ethnic diversity, democratic performance, and lethal violence are shaped by a complex interplay of historical, political, and socio-economic factors. While ethnic diversity coupled with systemic inequalities and weak institutions can exacerbate violence, inclusive democratic governance can reduce risks through policies promoting political participation, civil rights, and economic equality. This study focuses on understanding how ethnic and religious diversity, along with democratic performance, either exacerbate or mitigate lethal violence in the U.S.

Theoretical framework

Several theoretical frameworks provide valuable insights into understanding the dynamics of lethal violence in the context of socioeconomic and institutional factors. The selected theories emphasize the relationships between diversity, inequality, and democratic performance, offering a robust basis for the proposed model. Key theoretical frameworks underpinning this research include Relative Deprivation Theory (RDT), as outlined by Power et al. (2020), posits that perceived or actual inequalities between ethnic groups can fuel frustration and violence, particularly when groups feel excluded or marginalized. This is evident in the U.S., where systemic racial inequalities have historically fueled grievances among minority communities. Building on RDT, Systemic Racism Theory (SRT) emphasizes the deeply entrenched structures of inequality and discrimination that perpetuate disparities across racial and ethnic lines (Bonilla-Silva, 2021). Historical legacies of slavery and segregation in the U.S. have created enduring patterns of structural violence, as exemplified by movements like Black Lives Matter. These theories provide a robust foundation for understanding how institutional factors interact with diversity and democratic performance to influence levels of lethal violence.

The theoretical framework for this study is grounded in the distinction between two key measures of diversity and their distinct mechanisms for influencing violence. Ethnic and religious fractionalization, which represents a society with many distinct groups, is theorized to impact violence through a lack of social capital. In such a fragmented landscape, the absence of bridging ties between groups can undermine collective action and make it difficult for communities to foster trust and social cohesion, thereby creating an environment where violence is more likely to escalate. Conversely, polarization, which describes a society split into a few large, opposing groups, is linked to social identity theory and group threat theory. This dynamic foster a stronger "us versus them" mentality, intensifying inter-group competition for resources and power and increasing the likelihood of direct conflict and violence. We also recognize that in polarized communities, intra-group support networks can have a dual effect; they may moderate violence by providing a sense of belonging and support, or they can exacerbate it by reinforcing a collective identity in oppo-

sition to an out-group. Furthermore, our model distinguishes between democratic performance measures to clarify their specific roles. While electoral competitiveness provides a basic incentive for leaders to be responsive, it is the deliberative quality of governance that is a key moderating factor for violence. Deliberative quality provides the essential mechanism a legitimate and transparent channel for groups to air grievances and negotiate solutions, thereby reducing the need for lethal force as a means of conflict resolution.

The Stream Analogy of Lethal Violence (SALV) posits that homicide and suicide are alternative outcomes of a single stream of lethal violence within society (Unnithan et al., 1994). Recent research has expanded on this analogy, emphasizing cultural and socio-economic factors that influence the direction of this violence (Chon, 2013, 2016, 2017; Tuttle, 2018). Cultural variables, such as religiosity (Chon, 2016, 2017) and interpersonal restraint (Fridel & Zimmerman, 2019), as well as economic factors like world-system position, economic growth, and income inequality, have been linked to lethal violence outcomes. For instance, socioeconomic development correlates positively with suicide rates (Lester, 2009; Stack & Kposowa, 2008) and negatively with homicide rates (Chon, 2016, 2017; Whitt, 2010).

Key factors, including democratization (Clark, 2012), income inequality (Lee & Bean, 2004; Mahutga et al., 2011), and economic output (Valdimarsdóttir, 2018), shape violence patterns. Economic recessions often increase suicide rates, especially among high-status individuals (Henry & Short, 1954), whereas economic booms tend to elevate homicide rates, particularly among low-status individuals. The SALV framework highlights how frustration-aggression dynamics manifest as either suicide or homicide, depending on societal conditions. Systemic frustrations, such as poverty, unemployment, and family disruption, also significantly contribute to these outcomes (Unnithan et al., 1994).

Blanchflower (2021) noted that economic development, while associated with subjective well-being, also leads to higher suicide rates in advanced countries like Ireland, Switzerland, and the U.S. This aligns with Daly et al. (2001) happiness-suicide paradox, where individuals in happier countries may feel increased pressure to conform, elevating suicide rates. Stack and Kposowa (2008) and Chon (2013) further investigated income inequality's dual impact on violence, finding that disadvantaged individuals in unequal societies tend toward homicide, while those in equal societies lean toward suicide. Welch (2024) and Kollmeyer (2024) highlight globalization as a complicating factor, fostering inequality and sometimes inciting violent resistance, particularly in developing nations.

The SALV framework provides a dynamic perspective by linking ethnic diversity, democratic performance, and lethal violence as interconnected processes. Ethnic diversity introduces potential tensions, while democratic performance can either mitigate or exacerbate these tensions. Historical events, such as civil rights advancements or institutional repression, are interpreted as shifts in this stream. This framework is especially useful for understanding long-term trends in the U.S., including the interplay of ethnic diversity and democratic performance from 1945 to 2023, and their cumulative effects on violence (Fig. 3).

Based on these theoretical perspectives, this study follows the model proposed by Amin (2021), Amin and Ahmad (2018), and Moroskoski et al. (2022) and incorpo-

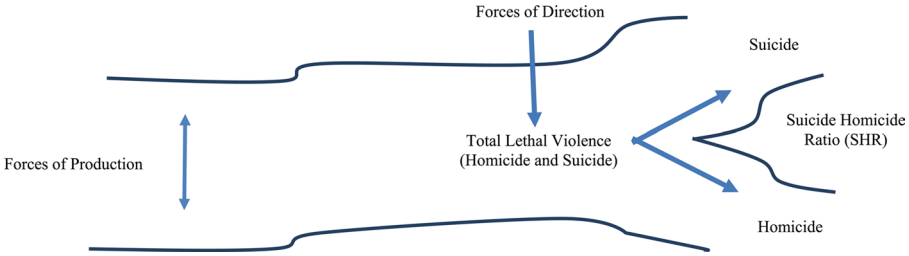

Fig. 3 Visual representation of the stream analogy of lethal violence. Source: Tuttle (2013) and Lanier (2010)

rates key socioeconomic variables to empirically analyze lethal violence. The functional relationship is expressed as:

$$\begin{aligned}&\text{Lethal Violence}\\&= \text{F (Diversity, Unemployment, Income inequality, GDP per capita, Democratic performance)}\end{aligned} \quad (1)$$

$$LV_t = \alpha_0 + \beta_1 (DIV)_t + \beta_2 (UN)_t + \beta_3 (GINI)_t + \beta_4 (gdppc)_t + \beta_5 (DP)_t \quad (2)$$

$$Suicides_t = \alpha_0 + \beta_1 (DIV)_t + \beta_2 (UN)_t + \beta_3 (GINI)_t + \beta_4 (gdppc)_t + \beta_5 (DP)_t \quad (3)$$

$$Homicides_t = \alpha_0 + \beta_1 (DIV)_t + \beta_2 (UN)_t + \beta_3 (GINI)_t + \beta_4 (gdppc)_t + \beta_5 (DP)_t \quad (4)$$

This study is based on the above three Eqs. (2, 3, and 4) for the empirical analysis of lethal violence. Equation (2) represents lethal violence as a combination of suicides and homicides, while Eqs. (3) and (4) separately examine suicides and homicides, respectively.

Data sources and methodology

Data source

This study uses time series data from the United States covering the period from 1945 to 2023. The dependent variable is lethal violence, defined as a combination of suicides and homicides. The data on lethal violence is collected from the WHO's mortality database. For the main explanatory variables, this study examines ethnic and religious diversity, measured in two different ways: the fractionalization index and the polarization index. For fractionalization, this study follows the methodology of Alesina et al. (2003) and uses the following formula;

$$FRACT_j = 1 - \sum_{i=1}^{N} V_{ij}^2 \quad (5)$$

where Vij is the share of group i in the total population of country j, where i = 1,…,N. Theoretically, the ethnic fractionalization index reflects the likelihood that two peo-

ple chosen at random within a given country will be from different ethnic groups. The measure ranges from 0, when there is no ethnic fractionalization and all individuals belong to the same ethnic group, to 1, when everyone belongs to their own ethnic group (Alesina et al., 2003; Montalvo & Reynal-Querol, 2005). For polarization, this study uses the polarization index, which focuses on the extent to which a population is polarized into distinct groups with significant inter-group tensions. The polarization index, as defined by Montalvo and Reynal-Querol (2005), is given by the following formula;

$$POL_j = \sum_{i=1}^{N} \sum_{j=1}^{N} p_i p_j \left| p_i - p_j \right| \tag{6}$$

where: N is the number of ethnic groups in the population, and p_i and p_j are the proportions of the population belonging to the ith and jth ethnic groups, respectively. This measure gives higher weights to distributions where groups are of similar sizes, as these configurations are more likely to result in polarization. The data on ethnic diversity were taken from the Database of the Cline Center for Democracy and the World Values Survey.

Control variables include unemployment, income inequality, GDP per capita, and democratic performance. Data on unemployment, income inequality, and GDP per capita are collected from the U.S. Bureau of Labor Statistics and the U.S. Bureau of Economic Analysis. Democratic performance is assessed using Principal Component Analysis (PCA) based on five indices provided by the Varieties of Democracy (V-Dem) database, accessible at www.v-dem.net. These indices, ranging from 0 to 1, capture the complexity of democracy beyond mere electoral processes, with higher values indicating better democratic quality. The V-Dem framework identifies five core principles of democracy: electoral, liberal, deliberative, egalitarian, and participatory. The electoral component ensures government responsiveness through competitive elections, while the liberal component protects individual and minority rights through civil liberties, rule of law, and checks on executive power. The deliberative principle emphasizes informed and reasonable dialogue in political decision-making, and the egalitarian component highlights the need to address inequalities to enhance political equality. The participatory principle underscores citizen involvement in political processes, including non-electoral forms of participation. Democracy plays a significant role in fostering financial development, but its benefits are maximized when supported by strong economic institutions, independent bureaucracies, and decentralized governance. Conversely, weak institutions may limit these positive effects. For more details, see Table 1 for variable descriptions and data sources.

Methodology

In time series data analysis, it is essential that all variables in the regression are stationary. If non-stationary data and residuals are used in an Ordinary Least Squares (OLS) regression, the results may lead to spurious regression outputs. To address this issue, the stationarity of variables is tested for the presence of a unit root. The

Table 1 Description of variables used in the regression analysis

Variable type	Symbol	Variable description/definition	Database used
Dependent variables: lethal violence			
Lethal violence	LV	The number of suicides plus homicides per 100,000 persons per year.	WHO Mortality Database
Suicides	S	The number of suicide deaths (self-harm deaths) per 100,000 persons per year.	
Homicides	H	The number of homicide deaths (violence deaths) per 100,000 persons per year.	
Main explanatory variables: Diversity (DIV)			
Ethnic fractionalization	EF	Measures the probability that two individuals randomly selected from a population belong to different ethnic groups.	Cline Center for Democracy, World Values Survey
Ethnic polarization	EP	Measures the extent to which a population is polarized into distinct ethnic groups with significant inter-group tensions.	
Religious fractionalization	RF	Measures the probability that two individuals randomly selected from a population belong to different religious groups.	
Religious polarization	RP	Measures the extent to which a population is polarized into distinct religious groups with significant inter-group tensions.	
Control variables			
Unemployment rate	UN	The percentage of the labor force that is unemployed but actively seeking employment.	US Bureau of Labor Statistics, US Bureau of Economic Analysis
Gini coefficient	GINI	A measure of income inequality within a population, where 0 indicates perfect equality and 1 indicates maximum inequality.	
GDP per capita growth	GDPPC	The growth rate of GDP per capita, which is used as an indicator of economic performance.	
Democratic Performance	DP	A composite measure of democracy based on five indices: electoral, liberal, deliberative, egalitarian, and participatory, ranging from 0 to 1, where higher values indicate better democratic quality.	Varieties of Democracy (V-Dem) Database

Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) tests are modified versions of the Dickey-Fuller (DF) test and are commonly used to determine whether a variable is stationary. To account for autocorrelation in the basic DF test, the ADF test includes lagged dependent variables. Additionally, the KPSS test is employed for robustness and is particularly useful in complementing the ADF and PP tests. While the ADF and PP tests are designed to test the null hypothesis of a unit root (non-stationarity), the KPSS test assumes stationarity as the null hypothesis. This distinction makes the KPSS test especially effective for verifying known stationary or non-stationary variables, as it provides a more comprehensive understanding of the stationarity properties in time series data.

ARDL bounds testing approach was first developed by Pesaran et al. (1999) and later extended by Pesaran et al. (2001). This method has several advantages over other co-integration techniques of Johansen and Juselius (1990) and Engle and Granger (1987). These co-integration techniques rely on the assumption of strictly I (1) variables (integrated order one). The requirement of the I (1) variables makes the estimate of the co-integration test subject to biases, since the order of integration of the variable depends upon the type of the unit root test and lag length selection. The ARDL bound testing approach does not impose the restriction that all variables under the study must be integrated in the same order. Therefore, the ARDL technique has the advantage of not requiring a specific identification of the order of the underlying data.

ARDL bounds testing approach (Pesaran et al., 2001) involves estimate using the Unrestricted Error Correction Model (URECM), which is specified as:

$$\begin{aligned}\Delta \mathbf{LV_t} = {} & \alpha_0 + \beta_1 (LV)_{t-1} + \beta_2 (DIV)_{t-1} + \beta_3 (GINI)_{t-1} + \beta_4 (UN)_{t-1} + \beta_5 (GDPPC)_{t-1} \\ & + \beta_6 (DP)_{t-1} + \sum_{t=1}^{p} \phi_i \Delta (LV)_{t-1} + \sum_{t=0}^{q} \omega_i \Delta (DIV)_{t-1} + \sum_{t=0}^{q} \gamma_i \Delta (UN)_{t-1} \\ & + \sum_{t=0}^{q} \delta_i \Delta (GINI)_{t-1} + \sum_{t=0}^{q} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{q} \vartheta_i \Delta (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{7}$$

$$\begin{aligned}\Delta \mathbf{S_t} = {} & \alpha_0 + \beta_1 (S)_{t-1} + \beta_2 (DIV)_{t-1} + \beta_3 (GINI)_{t-1} + \beta_4 (UN)_{t-1} \\ & + \beta_5 (GDPPC)_{t-1} + \sum_{t=0}^{q} \gamma_i \Delta (UN)_{t-1} + \sum_{t=0}^{q} \delta_i \Delta (GINI)_{t-1} \\ & + \beta_6 (DP)_{t-1} + \sum_{t=1}^{p} \phi_i \Delta (S)_{t-1} + \sum_{t=0}^{q} \omega_i \Delta (DIV)_{t-1} \\ & + \sum_{t=0}^{q} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{q} \vartheta_i \Delta (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{8}$$

$$\begin{aligned}\Delta \mathbf{H_t} = {} & \alpha_0 + \beta_1 (H)_{t-1} + \beta_2 (DIV)_{t-1} + \beta_3 (GINI)_{t-1} \\ & + \beta_4 (UN)_{t-1} + \beta_5 (GDPPC)_{t-1} + \beta_6 (DP)_{t-1} \\ & + \sum_{t=1}^{p} \phi_i \Delta (H)_{t-1} + \sum_{t=0}^{q} \omega_i \Delta (DIV)_{t-1} + \sum_{t=0}^{q} \gamma_i \Delta (UN)_{t-1} \\ & + \sum_{t=0}^{q} \delta_i \Delta (GINI)_{t-1} + \sum_{t=0}^{q} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{q} \vartheta_i \Delta (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{9}$$

Whereas α_0 is drift, ε_t is the error term, β_i are the long-run coefficients, Δ is the first difference operator and p and q are optimal lag lengths (these could be either the same or different). where LV, S, H, are lethal violence, suicides, homicides, DIV represents the ethnic and religious diversity, UN, GINI, GDPPC and DP are unemploy-

ment, income inequality, GDP per capita and democratic performance, respectively. The optimal lags selection in the unrestricted ARDL model is based on the AIC and SC criterion. The F test is used for testing the existence of long-run relationship. When long-run relationship exist, F test indicates that which variable should be normalized. The "Null Hypothesis" for no co-integration among variables in Eqs. (7, 8 and 9) is H_0: $\beta1=\beta2=\beta3=\beta4=\beta5=\beta6=0$ against the "Alternative Hypothesis" H1: $\beta1\neq\beta2\neq\beta3\neq\beta4\neq\beta5\neq\beta6\neq0$.

If there is evidence of long-run relationship (co-integration) of the variables, moved to the long run coefficient which is expressed as under,

$$\begin{aligned}\mathbf{LV_t} = {} & \alpha_0 + \sum_{t=1}^{i=p1} \phi_i (LV)_{t-1} + \sum_{t=0}^{i=q1} \beta_1 (DIV)_{t-1} \\ & + \sum_{t=0}^{i=q2} \beta_2 (UN)_{t-1} + \sum_{t=0}^{i=q3} \beta_3 (GINI)_{t-1} \\ & + \sum_{t=0}^{i=q4} \beta_4 (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \beta_5 (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{10}$$

$$\begin{aligned}\mathbf{S_t} = {} & \alpha_0 + \sum_{t=1}^{i=p1} \phi_i (S)_{t-1} + \sum_{t=0}^{i=q1} \beta_1 (DIV)_{t-1} \\ & + \sum_{t=0}^{i=q2} \beta_2 (UN)_{t-1} + \sum_{t=0}^{i=q3} \beta_3 (GINI)_{t-1} \\ & + \sum_{t=0}^{i=q4} \beta_4 (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \beta_5 (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{11}$$

$$\begin{aligned}\mathbf{H_t} = {} & \alpha_0 + \sum_{t=1}^{i=p1} \phi_i (H)_{t-1} + \sum_{t=0}^{i=q1} \beta_1 (DIV)_{t-1} \\ & + \sum_{t=0}^{i=q2} \beta_2 (UN)_{t-1} + \sum_{t=0}^{i=q3} \beta_3 (GINI)_{t-1} \\ & + \sum_{t=0}^{i=q4} \beta_4 (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \beta_5 (DP)_{t-1} + \varepsilon_t \end{aligned} \tag{12}$$

The orders of the lags in the ARDL model are selected by either the Akaike Information Criterion (AIC) or the Schwarz Bayesian Criterion (SBC), before the selected model is estimated by Ordinary Least Squares (OLS). The ARDL specification of the short-run dynamics can be derived by constructing an Error Correction Model (ECM) of the following form:

$$\begin{aligned}\Delta\,\mathbf{LV_t} = {} & \alpha_0 + \sum_{t=1}^{1=p} \phi_i \Delta (LV)_{t-1} + \sum_{t=0}^{i=q1} \omega_i \Delta (DIV)_{t-1} \\ & + \sum_{t=0}^{i=q2} \gamma_i \Delta (UN)_{t-1} + \sum_{t=0}^{i=q3} \delta_i \Delta (GINI)_{t-1} \\ & + \sum_{t=0}^{i=q4} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \vartheta_i \Delta (DP)_{t-1} + \psi\, ECM_{t-1} + \varepsilon_t \end{aligned} \tag{13}$$

$$\Delta \mathbf{S_t} = \alpha_0 + \sum_{t=1}^{1=p} \phi_i \Delta (S)_{t-1} + \sum_{t=0}^{i=q1} \omega_i \Delta (DIV)_{t-1} + \sum_{t=0}^{i=q2} \gamma_i \Delta (UN)_{t-1} + \sum_{t=0}^{i=q3} \delta_i \Delta (GINI)_{t-1} + \sum_{t=0}^{i=q4} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \vartheta_i \Delta (DP)_{t-1} + \psi ECM_{t-1} + \varepsilon_t \quad (14)$$

$$\Delta \mathbf{H_t} = \alpha_0 + \sum_{t=1}^{1=p} \phi_i \Delta (H)_{t-1} + \sum_{t=0}^{i=q1} \omega_i \Delta (DIV)_{t-1} + \sum_{t=0}^{i=q2} \gamma_i \Delta (UN)_{t-1} + \sum_{t=0}^{i=q3} \delta_i \Delta (GINI)_{t-1} + \sum_{t=0}^{i=q4} \phi_i \Delta (GDPPC)_{t-1} + \sum_{t=0}^{i=q5} \vartheta_i \Delta (DP)_{t-1} + \psi ECM_{t-1} + \varepsilon_t \quad (15)$$

where ECMt-1 is the error correction term, defined as

$$\mathbf{ECM_t} = LV_{t-1} \ \alpha_0 - \sum_{t=1}^{i=p1} \beta_1 (LV)_{t-1} - \sum_{t=0}^{i=q1} \beta_2 (DIV)_{t-1} - \sum_{t=0}^{i=q2} \beta_3 (UN)_{t-1} - \sum_{t=0}^{i=q3} \beta_4 (GINI)_{t-1} - \sum_{t=0}^{i=q4} \beta_5 (GDPPC)_{t-1} - \sum_{t=0}^{i=q5} \beta_6 (DP)_{t-1} \quad (16)$$

$$\mathbf{ECM_t} = S_{t-1} \ \alpha_0 - \sum_{t=1}^{i=p1} \beta_1 (S)_{t-1} - \sum_{t=0}^{i=q1} \beta_2 (DIV)_{t-1} - \sum_{t=0}^{i=q2} \beta_3 (UN)_{t-1} - \sum_{t=0}^{i=q3} \beta_4 (GINI)_{t-1} - \sum_{t=0}^{i=q4} \beta_5 (GDPPC)_{t-1} - \sum_{t=0}^{i=q5} \beta_6 (DP)_{t-1} \quad (17)$$

$$\mathbf{ECM_t} = H_{t-1} \ \alpha_0 - \sum_{t=1}^{i=p1} \beta_1 (H)_{t-1} - \sum_{t=0}^{i=q1} \beta_2 (DIV)_{t-1} - \sum_{t=0}^{i=q2} \beta_3 (UN)_{t-1} - \sum_{t=0}^{i=q3} \beta_4 (GINI)_{t-1} - \sum_{t=0}^{i=q4} \beta_5 (GDPPC)_{t-1} - \sum_{t=0}^{i=q5} \beta_6 (DP)_{t-1} \quad (18)$$

All coefficients of short-run equations are coefficients relating to the short run dynamics of the model's convergence to equilibrium and ψ represents the speed of adjustment.

Empirical results

Table 2 presents the results of unit root tests, including the Augmented Dickey-Fuller (ADF), Phillips-Perron (PP), and Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests, for the stationarity of the variables in the models, both with and without a trend. The tests are conducted for the dependent variables (lethal violence, suicides, and homicides) and key explanatory variables, as well as for control variables. The table reports the test statistics at both the level and first difference. For the dependent variables, the ADF and PP tests indicate that all the variables (lethal violence, suicides,

Table 2 Test for unit Root, with trend and without trend

Variables	ADF without trend		ADF with trend		PP without trend		PP with trend		KPSS without trend		KPSS with trend	
	Test Statistic		Test Statistic		Test Statistic		Test Statistic		Test Statistic		Test Statistic	
	At level	1 st diff.	At level	1 st diff.	At level	1st diff.	At level	1st diff.	At level	1 st diff.	At level	1 st diff.
Dependent variables												
LV	−2.530	−9.078***	−1.765	−9.698***	−2.509	−9.076***	−1.556	−9.738***	0.997	0.0444	0.737	0.078
S	−0.537	−8.086***	−1.711	−7.973***	−0.747	−8.085***	−1.933	−7.973***	0.591	0.11	0.366	0.065
H	−1.250	−5.352***	−1.207	−5.306***	−1.499	−5.390***	−1.454	−5.338***	1.47	0.182	0.885	0.112
Main explanatory variables												
EF	−1.844	−6.367***	−2.123	−6.536***	−1.905	−6.796***	−2.021	−6.243***	1.151	0.170	0.284	0.137
EP	−1.820	−7.725***	−2.397***	−5.30***	−1.954	−6.911***	−4.311***	−7.379***	1.146	0.166	0.194	0.159
RF	−1.76***	−9.611***	−4.321	−9.30***	−2.011***	−8.50***	−2.480	−6.200**	1.206	0.162	0.083	0.150
RP	−1.838	−9.842***	−2.770	−5.71***	−1.840	−5.18***	−3.581	−8.466***	0.107	0.043	0.038	0.143
Control variables												
UN	−3.717***	−8.563***	−3.571**	−8.550***	−3.754***	−8.649***	−3.630**	−8.636***	0.431	0.0228	0.142	0.011
GINI	0.422	−8.000***	−2.699	−8.076***	0.419	−8.019***	−2.712	−8.098***	0.96	0.126	0.226	0.194
GDPPC	6.792	−3.746***	1.166	−5.946***	6.524	−3.521***	1.125	−5.689***	1.8	0.0846	.480	0.087
DP	−2.029	−7.095***	−0.016	−7.380***	−1.932	−7.129***	−0.240	−7.382***	1.48	0.103	.458	0.099

Source: Author's Calculation. *Represents a significance level of 0.10 (10%), ** indicates a significance level of 0.05 (5%), and *** denotes a significance level of 0.01 (1%). The ADF and PP tests refer to the Augmented Dickey-Fuller and Phillips-Perron tests, respectively, used to determine stationarity with and without a trend, at both the level and first difference. The Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test evaluates stationarity with the null hypothesis of stationarity. The critical values for this test depend on whether it is testing for level stationarity or trend stationarity. For level stationarity, the critical values at the 1%, 2.5%, 5%, and 10% significance levels are 0.739, 0.574, 0.463, and 0.347, respectively. For trend stationarity, the corresponding critical values are 0.216, 0.176, 0.146, and 0.119. If the test statistic exceeds the critical value, the null hypothesis of stationarity is rejected (Kwiatkowski et al., 1992)

and homicides) are non-stationary at the level, as their test statistics do not exceed the critical values, but they become stationary at the first difference, with all test statistics significantly less than the critical value at the 1% level (denoted by ***). This suggests that these variables are integrated of order one (I(1)). The KPSS test, with the null hypothesis of stationarity, provides a complementary perspective. For the dependent variables, the KPSS test results indicate non-stationarity at the level, as the test statistics exceed the critical values for level stationarity. However, at the first difference, the KPSS test confirms stationarity, as the test statistics are well below the critical values.

Turning to the main explanatory variables, the results show mixed outcomes. For ethnic fractionalization (EF), the ADF and PP tests suggest stationarity at the first difference in most cases, with the exception of the model with trend in the ADF and PP tests, where the variables are not stationary. The KPSS test confirms non-stationarity at the level but stationarity at the first difference. Similarly, for ethnic polarization (EP), religious fractionalization (RF), and religious polarization (RP), the results vary, with some variables showing stationarity at the first difference and others not. The KPSS test results further support the finding of non-stationarity at the level and stationarity at the first difference for most variables. For the control variables, the ADF and PP tests show that most variables (unemployment, Gini coefficient, GDP per capita, and dependency ratio) are non-stationary at the level but become stationary at the first difference, indicated by the significant test statistics at the 1% level (***). The KPSS test confirms the stationarity of these variables at the first difference as well, with the test statistics falling below the critical values for both level and trend stationarity.

These results suggests that the series are appropriate for further analysis, such as co-integration testing, in order to explore long-run relationships between the variables. This indicates the presence of long-term trends or evolving dynamics in these variables, which are stabilized after differencing. The results suggest that most variables are integrated of order one I(1) requiring first differencing to achieve stationarity, while a few, such as RF and UN, are stationary at the level I(0). These findings validate the use of an Autoregressive Distributed Lag (ARDL) model, which accommodates variables with mixed integration levels and provides a robust framework for analyzing short-term and long-term relationships.

ARDL model of lethal violence

Bound testing

Table 3 presents the results of the Bound F-testing, which is used to assess the presence of a long-run relationship between the variables in an Autoregressive Distributed Lag (ARDL) model. The critical values provided correspond to the lower and upper bounds at different significance levels (1%, 2.5%, 5%, and 10%). The lower bound represents the critical value for the null hypothesis of no long-run relationship (I(0)), while the upper bound represents the critical value for the alternative hypothesis of a long-run relationship (I(1)).

Table 3 Results of bound F-testing

	Critical values bounds			
Significance	1%	2.5%	5%	10%
Lower Bound I (0)	3.06	2.7	2.39	2.08
Upper Bound I (1)	4.15	3.73	3.38	3
Variables	F-calculated			Optimal lag selection
Lethal violence equation	I	22.85		(1,1,2,1,0,0)
	II	22.96		(1,0,1,0,0,0)
	III	23.06		(1,0,2,1,0,0)
	IV	22.57		(1,0,2,2,1,0)
Suicides equation	I	25.45		(1,2,3,0,2,0)
	II	25.38		(1,2,0,1,1,0)
	III	25.55		(1,2,1,2,2,0)
	IV	25.33		(1,1,2,2,1,0)
Homicides equation	I	23.06		(1,0,1,1,1,1)
	II	23.03		(1,2,0,2,1,1)
	III	23.08		(1,1,2,3,1,1)
	IV	22.82		(1,2,0,2,1,2)

Note:

1. I, II, III and IV, represent the model related to ethnic fractionalization, ethnic polarization, religious fractionalization and religious polarization, respectively

2. Lag selection is capped at 3 for each variable to avoid overfitting with annual data

3. F-Calculated refers to the ARDL Bounds Test statistic for each model. Critical values (5% significance): Lower bound = 2.39, Upper bound = 3.38

4. This table reports the ARDL lag selection used in the bounds testing procedure

Table 3 presents the results of the Bound F-testing, which evaluates whether there is a long-run relationship between the variables in the lethal violence, suicides, and homicides equations. The F-statistics calculated for each model (I to IV) are compared against critical value bounds at different significance levels. These bounds are divided into two categories: the lower bound (I) for no co-integration (0) and the upper bound (I) for co-integration (1). In the lethal violence equation, the F-statistics for all model specifications (I to IV) are well above the upper bound at the 1% significance level, with values ranging from 22.57 to 23.06. The upper bound at the 1% level is 4.15, so these results strongly suggest the presence of a long-run relationship between the variables included in the lethal violence equation, such as diversity measures and other control variables. Similarly, the F-statistics for the suicides equation also exceed the upper critical value of 4.15 at the 1% significance level. With F-statistics ranging from 25.33 to 25.55, the results indicate that there is a significant long-run relationship between the explanatory variables and suicides, regardless of whether ethnic fractionalization, ethnic polarization, religious fractionalization, or religious polarization is considered. The results for the homicides equation follow a similar pattern, with F-statistics ranging from 22.82 to 23.08, all of which are above the upper critical bound of 4.15 at the 1% significance level. This provides strong evidence of a long-run relationship between the variables in the homicide model as well.

The calculated F-statistics for all three equations exceed the upper bound critical value at the 1% significance level. This suggests that there is a long-run equilibrium relationship between the dependent variables (lethal violence, suicides, and homicides) and the independent variables included in the models. The results from the Bound F-test support the notion that the models used are appropriate for analyzing the long-term dynamics of violence and that the variables are co-integrated.

Co-Integration and long run form

After showing the result of bound testing, the presence of long run relationship exists among the variables. ARDL technique by using auto-selection of lags length is selected on the basis on Akaike Information Criteria (AIC). The result of long run is shown in Table 4.

Table 4 presents the estimated long-run coefficients for lethal violence, suicides, and homicides using the ARDL approach. The coefficients reflect the long-term relationships between the dependent variables (lethal violence, suicides, and homicides) and the explanatory variables, including ethnic and religious diversity, unemployment rate, income inequality, GDP per capita, and democratic performance.

In the lethal violence equation, the lagged value of lethal violence (LV (−1)) is consistently significant across all specifications, with coefficients ranging from 0.636 to 0.727, indicating that past levels of lethal violence have a strong influence on current levels. The primary finding is that all diversity measures have a positive and statistically significant long-run effect on all forms of violence. The coefficients of 5.325 for ethnic fractionalization (EF), 4.401 for ethnic polarization (EP), 7.144 for religious fractionalization (RF), and 6.793 for religious polarization (RP) demonstrate that a typical, real-world increase in diversity (e.g., a one-standard-deviation increase) is associated with a meaningful long-run increase in lethal violence. However, the unemployment rate (UN), Gini coefficient (GINI) and GDP per capita growth (GDPPC) not appear to have a strong impact on lethal violence, with coefficients being statistically insignificant. Democratic performance (DP) consistently shows a negative relationship with lethal violence, with coefficients ranging from −0.045 to −0.37, suggesting that better democratic governance helps reduce lethal violence.

In the suicides equation, the lagged suicide variable (LV (−1)) also shows a significant and positive effect across all specifications, with coefficients 0.704, 0.738, 0.759, and 0.578, indicate a strong historical persistence in suicide rates. The finding for the suicides equation is that all diversity measures have a positive and statistically significant long-run effect on suicide rates. The coefficients of 1.122 for ethnic fractionalization (EF), 8.215 for ethnic polarization (EP), 1.406 for religious fractionalization (RF), and 3.558 for religious polarization (RP) demonstrate that a typical, real-world increase in diversity (e.g., a one-standard-deviation increase) is associated with a meaningful long-run increase in suicides. The socioeconomic variables reveal a deeper picture. The unemployment rate (UN) consistently has a positive and significant effect on suicides, with coefficients of 0.111, 0.123, 0.127, and 0.085. This confirms a strong link between joblessness and increased suicide rates. In contrast, the Gini coefficient (GINI), a measure of income inequality, shows a negative

Table 4 Estimate long run coefficients by using ARDL approach

Variable	Lethal violence Equation				Suicides Equation				Homicides Equation			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
LV (−1)	0.674***	0.655***	0.636***	0.727***	0.704***	0.738***	0.759***	0.578***	0.880**	0.867***	0.868***	0.867***
	(0.092)	(0.095)	(0.098)	(0.082)	(0.080)	(0.086)	(0.088)	(0.102)	(0.067)	(0.068)	(0.068)	(0.066)
EF	5.325***				1.122***				1.485**			
	(4.311)				(0.615)				(0.747)			
EP		4.401***				8.215***				10.51**		
		(3.035)				(4.712)				(7.124)		
RF			7.144**				1.406***				1.656***	
			(4.401)				(0.725)				(1.058)	
RP				6.793**				3.558***				1.856***
				(1.207)				(2.126)				(1.258)
UN	0.091	0.167	0.194	0.118	0.111***	0.123***	0.127***	0.085**	0.099**	0.080**	0.074*	0.057**
	(0.177)	(0.180)	(0.182)	(0.227)	(0.026)	(0.026)	(0.026)	(0.032)	(0.039)	(0.040)	(0.041)	(0.025)
GINI	−0.077	−0.208	−0.222	−0.181	−0.102*	−0.125**	−0.127*	−0.048**	−0.127*	−0.162**	−0.166**	−0.156
	(0.306)	(0.298)	(0.297)	(0.416)	(0.043)	(0.041)	(0.041)	(0.061)	(0.067)	(0.066)	(0.066)	(0.054)
GDPPC	−0.0002	−0.0001	−0.0001	−6.29E	−3.16E	−8.41E	7.27E	−1.38E	−6.43E	−3.49E	−1.36E	−1.36E
	(0.0002)	(0.0001)	(8.51E)	(0.0001)	(3.01E)	(1.91E)	(1.15E)	(2.26E)	(4.96E)	(3.31E)	(2.19E)	(2.19E)
DP	−0.045**	−0.205***	−0.25***	−0.37***	−0.03**	−0.089***	−0.123**	−0.204**	−0.065**	−0.033*	−0.017**	−0.073**
	(0.421)	(0.517)	(0.506)	(0.413)	(0.074)	(0.105)	(0.112)	(0.092)	(0.137)	(0.152)	(0.155)	(0.145)
C	−5.000	−7.883	−25.26	17.13	3.533	2.821	−1.190	−21.21	2.556	2.596	−1.381	−1.345
	(17.61)	(17.59)	(25.31)	(103.7)	(2.913)	(3.315)	(4.886)	(17.27)	(4.042)	(4.105)	(6.139)	(4.145)
R2	0.842	0.844	0.845	0.838	0.911	0.910	0.911	0.910	0.958	0.958	0.958	0.958
Adjusted R2	0.826	0.828	0.829	0.822	0.901	0.900	0.902	0.900	0.953	0.953	0.953	0.953
D-W	2.100	2.088	2.063	2.189	2.171	2.218	2.281	1.926	1.662	1.657	1.666	1.665
F-Stat	52.65	53.24	53.79	51.07	93.98	93.48	94.75	93.06	210.3	209.8	210.8	210.5
Prob. F Stat	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000

Notes: Each column presents the results from separate regression. The standard errors in parentheses. ***Shows the 1% Significance of coefficients, ** Shows the 5% significance of coefficients, * Shows the 10% significance of coefficient

and significant relationship with suicides, which is an interesting finding that may warrant further discussion. Finally, GDP per capita (GDPPC) has coefficients that are extremely small and statistically insignificant, suggesting that broad economic growth does not have a strong direct impact on suicides over the long run. The most compelling finding, from a policy perspective, is the consistent role of democratic performance (DP). With negative and significant coefficients ranging from −0.03 to −0.204, democratic performance serves as a key mitigating factor, consistently reducing suicide rates over the long run.

In the homicide's equation, the lagged homicides variable (LV (−1)) again shows a significant and positive effect, with coefficients ranging from 0.578 to 0.880, indicate a strong historical persistence in homicides. The finding for the Homicides Equation is that all diversity measures have a positive and statistically significant long-run effect on homicide rates. The coefficients of 1.485 for ethnic fractionalization (EF), 10.51 for ethnic polarization (EP), 1.656 for religious fractionalization (RF), and 1.856 for religious polarization (RP) demonstrate that a typical, real-world increase in diversity (e.g., a one-standard-deviation increase) is associated with a meaningful long-run increase in homicides. In direct contrast to these findings, the most crucial policy-relevant result is the consistent role of democratic performance (DP). With negative and significant coefficients ranging from −0.065 to −0.073, democratic performance serves as a powerful mitigating factor, consistently reducing homicide rates over the long run. Regarding socioeconomic factors, the unemployment rate (UN) consistently has a positive and significant effect on homicides, with coefficients ranging from 0.057 to 0.099, confirming a strong link between joblessness and increased homicide rates. The Gini coefficient (GINI), a measure of income inequality, shows a largely negative relationship with homicides, while GDP per capita (GDPPC) has coefficients that are extremely small and statistically insignificant, suggesting that broad economic growth has a minimal direct impact on homicide rates in the long run.

Ethnic and religious diversity, particularly in terms of fractionalization and polarization, consistently show significant positive effects on lethal violence, suicides, and homicides. Our findings align with Basedau et al. (2016), who show that religious factors, such as identity overlap and grievances within religious groups, contribute to the onset of armed conflict. They also note that the impact varies depending on whether conflicts are religiously motivated. Chon (2012) finds that ethnic and linguistic heterogeneity increase homicide rates, while religious heterogeneity does not. The study also concludes that the interaction between population heterogeneity and income inequality does not significantly affect homicide rates. Additionally, Ray and Esteban (2017) argue that conflict is often driven by economic inequalities and ethnic differences, particularly in developing countries, highlighting the complex relationship between economic development and social unrest. Additionally, better democratic performance is consistently linked to lower levels of violence across all types, emphasizing the role of governance in reducing violent behaviors (Hegre & Nome, 2010).

While economic theory often links broad economic downturns to peaks in suicide rates, our findings suggest that the influence of GDP per capita growth on lethal violence is minimal in our long-run models. This result, seemingly at odds with estab-

lished economic theory, can be explained by our more granular findings. The effect of economic conditions on lethal violence appears to be channeled through more direct and proximate measures of economic distress. Our analysis shows that the unemployment rate (UN) and the Gini coefficient (GINI) have significant, though sometimes complex, effects on the individual components of lethal violence, such as suicides and homicides. This suggests that the broad measure of GDP growth may not be a sufficiently precise indicator of the economic hardship that drives violence. Instead, more specific variables that capture joblessness and income inequality provide a clearer picture of how economic conditions affect lethal violence in the long run.

Error correction representation of ARDL model

The results of the Error Correction Model (ECM) for lethal violence, suicides and homicides are presented in Table 5. Most of the coefficients in the ECM are insignificant, except for lag difference of ethnic and religious diversity.

Table 5 presents the results of the error correction representation for the selected ARDL models for lethal violence, suicides, and homicides equations. These results focus on short-term dynamics, and the coefficients reflect the short-term adjustments to deviations from long-run equilibrium. The analysis of lethal violence reveals that ethnic fractionalization (D(EF)) significantly increases lethal violence in the short run, as indicated by a coefficient of 3.142 in Specification I. Other diversity measures, such as ethnic polarization (D(EP)), religious fractionalization (D(RF)), and religious polarization (D(RP)), also show significant positive effects in different model specifications. This suggests that both ethnic and religious diversity contribute to increased lethal violence under certain conditions. Among the control variables, unemployment rate (D(UN)), income inequality (D(GINI)), GDP per capita growth (D(GDPPC)), and democratic performance (D(DP)) exhibit no significant short-run effects on lethal violence across the specifications.

In the suicide's equation, both ethnic and religious diversity measures (D(EF), D(EP), D(RF), and D(RP)) have consistently significant and positive effects across specifications. This indicates that increasing diversity is associated with higher suicide rates in the short run. Among the control variables, unemployment rate (D(UN)) emerges as a significant positive determinant, suggesting that rising unemployment exacerbates suicide rates. Income inequality (D(GINI)), however, shows limited and weak significance, with only one specification indicating a slight negative relationship. Other control variables, such as D(GDPPC) and D(DP), remain insignificant. The results for homicides suggest that diversity measures, including D(EF), D(EP), D(RF), and D(RP), significantly increase homicide rates, albeit with smaller magnitudes compared to their effects on suicides. This finding highlights the role of diversity in influencing different forms of violence. Control variables, including unemployment rate (D(UN)) and income inequality (D(GINI)), do not exhibit significant short-run effects on homicide rates. Similarly, D(GDPPC) and D(DP) remain consistently insignificant.

The error correction term (CointEq(−1)) is negative and highly significant across all equations and specifications, confirming the existence of a stable long-run relationship. The speed of adjustment to the long-run equilibrium varies: for lethal vio-

Table 5 Error correction representation for the selected ARDL model

Variable	Lethal violence equation				Suicides equation				Homicides equation			
	I	II	III	IV	I	II	III	IV	I	II	III	IV
D(EF)	3.142***				0.809***				0.593***			
	(0.561)				(0.223)				(0.145)			
D(EP)		1.634***				0.682***				0.323***		
		(0.291)				(0.188)				(0.191)		
D(RF)			1.054***				0.674***				0.116***	
			(0.204)				(0.119)				(0.231)	
D(RP)				1.32***				0.438***				0.473***
				(0.232)				(0.162)				(0.265)
D(UN)	−0.349	−0.350	−0.335	−0.351	0.089**	0.090**	0.090**	0.063*	−0.076	−0.078	−0.078	−0.064
	(0.281)	(0.266)	(0.258)	(0.263)	(0.042)	(0.040)	(0.038)	(0.035)	(0.065)	(0.062)	(0.059)	(0.057)
D(GINI)	0.229	0.172	0.261	0.362	−0.137	−0.156*	−0.128	−0.089	0.026	−0.002	0.040	0.058
	(0.544)	(0.542)	(0.543)	(0.545)	(0.082)	(0.083)	(0.080)	(0.072)	(0.122)	(0.122)	(0.120)	(0.114)
D(GDPPC)	−0.0006	−0.0006	−0.0005	−0.0003	−8.90E	−9.16E	−8.15E	−6.80E	−4.13E	−5.72E	−3.95E	−3.12E
	(0.0005)	(0.0004)	(0.0003)	(0.0003)	(7.91E)	(6.72E)	(5.15E)	(4.07E)	(0.0001)	(9.65E)	(7.27E)	(6.29E)
D(DP)	−0.559	−0.484	−0.590	−0.265	−0.051	−0.0006	−0.031	0.103	−0.180	−0.202	−0.205	−0.322
	(0.956)	(0.973)	(0.092)	(0.924)	(0.141)	(0.144)	(0.142)	(0.122)	(0.212)	(0.218)	(0.218)	(0.193)
CointEq(−1)	−0.451***	−0.466***	−0.468***	−0.39***	−0.34***	−0.31***	−0.33***	−0.58***	−0.12***	−0.13***	−0.116***	−0.157***
	(0.084)	(0.087)	(0.987)	(0.069)	(0.065)	(0.059)	(0.059)	(0.084)	(0.022)	(0.025)	(0.021)	(0.023)

Note: It presents the short-run dynamics and adjustment to long-run equilibrium for three dependent variables: lethal violence, suicides, and homicides, under four model specifications (I, II, III, IV). The variables are differenced (denoted by "D") to capture the short-term effects of the changes in each explanatory variable, and the error correction term (CointEq(−1)) reflects the speed of adjustment to the long-run equilibrium. ***Shows the 1% significance of coefficients, ** Show the 5% significance of the coefficients and * Show the 10% significance of the coefficients

lence, it ranges between 39% and 46% per period; for suicides, it is faster, ranging from 31% to 58%; and for homicides, the adjustment rate is slower, ranging between 12% and 15% per period. These values indicate that while short-term deviations occur, the system consistently reverts to its equilibrium over time.

Results of diagnostic tests

Table 6 represents the diagnostic tests to evaluate the robustness of regression models for lethal violence, suicides, and homicides equations. These tests assess the presence of serial correlation, the normality of residuals, and heteroscedasticity to ensure the models meet key econometric assumptions. The results indicate that the models are well-specified and suitable for statistical inference. The Breusch-Godfrey LM test was employed to assess serial correlation in the residuals. Across all equations and model specifications (I-IV), the test yielded p-values greater than 0.05, indicating no evidence of serial correlation. This suggests that the residuals are independent over time, enhancing the reliability of the parameter estimates and ensuring the validity of inferences drawn from the models. The Jarque-Bera test was used to evaluate the normality of residuals. For all three equations, the statistics were consistently low, with no significant deviations from normality observed. This result implies that the residuals are approximately normally distributed, satisfying a key assumption for many statistical tests and justifying the use of standard inference techniques in the analysis. The presence of heteroscedasticity was assessed using the Breusch-Godfrey LM test. For all equations and model specifications, the p-values exceeded the 0.05 threshold, indicating no evidence of heteroscedasticity. This finding confirms that the variance of residuals is constant across observations, which is crucial for unbiased and efficient estimates in regression models. These diagnostic test results suggest that the regression models for Lethal Violence, Suicides, and Homicides equations meet essential econometric assumptions. The absence of serial correlation, the normality of residuals, and the lack of heteroscedasticity collectively affirm the robustness and reliability of these models for policy analysis and empirical research.

Table 7 evaluates the joint Wald test for Democratic Performance (DP) coefficient stability across our specifications. The results, with a p-value of 0.117 for the comparison between models I and II and 0.159 for models III and IV, show that we fail to reject the null hypothesis that the coefficients are equal. This confirms that the variation in the DP coefficient magnitudes is not statistically meaningful. Therefore, we can conclude with greater confidence that the mitigating effect of democratic performance on lethal violence is statistically stable and robust across our different model specifications.

Stability of the model

Figure 4 illustrates the stability of the ARDL models across the different equations i.e., lethal violence, suicides, and homicides under various model specifications (I, II, III, and IV). The diagnostic graphs for both the CUSUM and CUSUMQ tests show that the residual lines for all equations and specifications remain within the critical bounds at the 5% significance level. This suggests that, based on the CUSUM and

Table 6 Diagnostic tests

Variable		Serial correlation (Breusch-Godfrey LM Test)		Normality (Jarque-Bera Test)		Heteroscedasticity (Breusch-Godfrey LM Test)	
		LM Version	F Version	LM Version	F Version	LM Version	F Version
Lethal violence Equation	I	2.9243	F(2,50) 0.4629	0.1240	n/a	5.7124	F(11,52) 0.4857
	II	2.5370	F(2,50) 0.4892	0.1225	n/a	5.6565	F(11,52) 0.4275
	III	2.6245	F(2,50) 0.4824	0.1291	n/a	5.4989	F(11,52) 0.4505
	IV	5.3425	F(2,50) 0.4079	0.1306	n/a	6.8173	F(11,52) 0.4475
Suicides Equation	I	0.4796	F(11,49) 0.622	0.1533	n/a	0.9174	F(11,49) 0.5314
	II	0.7350	F(2,47) 0.4849	0.1320	n/a	0.9352	F(11,49) 0.5156
	III	0.8061	F(2,47) 0.4526	0.1880	n/a	0.9744	F(11,49) 0.4816
	IV	0.4044	F(2,47) 0.6696	0.1402	n/a	1.7157	F(11,49) 0.3976
Homicides Equation	I	3.4818	F(2,47) 0.3389	0.4804	n/a	2.8412	F(11,49) 0.2159
	II	3.5044	F(2,47) 0.3381	0.2755	n/a	2.7090	F(11,49) 0.2283
	III	3.0177	F(2,47) 0.3585	0.4940	n/a	2.8831	F(11,49) 0.2553
	IV	0.2260	F(2,47) 0.3986	0.8174	n/a	2.7994	F(11,49) 0.2566

Note: The null hypotheses for the diagnostic tests conducted are as follows. For the serial correlation test (Breusch-Godfrey LM test), the null hypothesis asserts that there is no serial correlation in the residuals, indicating that the errors are not correlated over time. In the case of the normality test (Jarque-Bera test), the null hypothesis posits that the residuals are normally distributed. Lastly, for the heteroscedasticity test (Breusch-Godfrey LM test), the null hypothesis assumes that there is no heteroscedasticity, meaning the residuals have a constant variance across observations. The F version of the normality test is not applicable (n/a) because it is used for testing variance equality, not normality. Normality is assessed using the Jarque-Bera test, which checks skewness and kurtosis of residuals

Table 7 Joint Wald test for Democratic performance (DP) coefficient stability

Test	Test statistic	*p*-value	Interpretation
$HO: \beta_{DP,I} = \beta_{DP,II}$	$\chi^2 = 2.45$	0.117	Fail to reject HO
$HO: \beta_{DP,III} = \beta_{DP,IV}$	$\chi^2 = 1.98$	0.159	Fail to reject HO

Note: The table presents the results of a joint Wald test to assess the statistical stability of the long-run Democratic Performance (DP) coefficients. The null hypothesis (H0) for each test is that the long-run coefficients are equal across the specified models. A p-value greater than 0.05 indicates that we fail to reject the null hypothesis, confirming that the observed differences in the coefficients are not statistically significant.

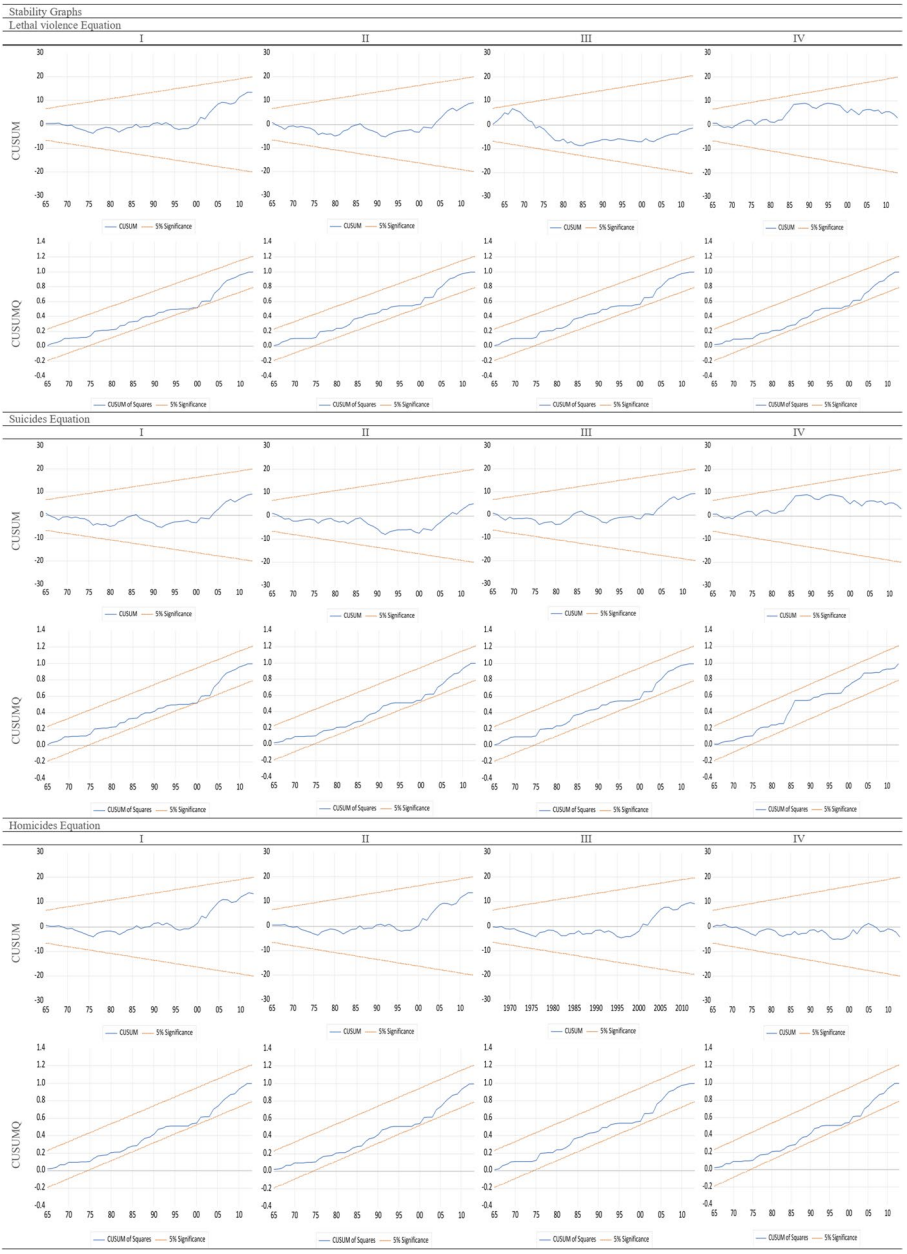

Fig. 4 Diagnostic Graphs for Stability (CUSUM & CUSUMQ). Note: CUSUM and CUSUMQ tests utilize to assess model stability. If the blue lines (representing cumulative sums) remain within the red critical bounds, the model is stable, indicating consistent relationships between variables over time. Exceeding these bounds suggests potential instability and changes in these relationships (Halicioglu, 2007)

CUSUMQ tests, all the models are stable over time. Specifically, both the cumulative sum of recursive residuals (CUSUM) and the cumulative sum of squares of recursive residuals (CUSUMQ) indicate no evidence of systematic changes in the model coefficients or the variance of the residuals, confirming the stability of the ARDL models across the different specifications tested.

Discussion

The results of our long-run and short-run models provide a robust and nuanced understanding of the factors influencing lethal violence, suicides, and homicides in the United States from 1945 to 2023. Our primary finding, consistent across all three violent outcomes, is the significant positive association between ethnic and religious diversity, in both fractionalization and polarization, and increased violence. This finding is particularly relevant to relative deprivation theory, which posits that a perceived discrepancy between what individuals or groups believe they are entitled to and what they actually possess can lead to frustration and, in some cases, violent behavior. In diverse societies, this can manifest as inter-group competition for resources, status, and power, which in turn fuels the tensions observed in our models. Furthermore, our findings on diversity can be contextualized by the theory of systemic racism, which suggests that deeply embedded discriminatory practices and policies create and perpetuate inequalities across different racial and ethnic groups. These institutional barriers can exacerbate feelings of relative deprivation, leading to a breakdown of social cohesion and trust, which our findings show is associated with increased lethal violence, suicides, and homicides.

This aligns with existing theories on social cohesion and conflict, suggesting that societal divisions contribute to a breakdown of social trust and stability, which in turn elevates the risk of violence. Specifically, our findings support Basedau et al.s' (2016) argument that religious factors can influence conflict, and corroborate Chon's (2012) conclusion that ethnic heterogeneity is a significant predictor of violence.

A key finding of this study is the consistent negative relationship between democratic performance and all forms of violence. The strong, significant coefficients for democratic performance (DP) in both the long-run and short-run models suggest that effective and accountable governance is a powerful mitigating factor. This supports the work of Hegre and Nome (2010), who argue that strengthening democratic institutions can reduce the prevalence of civil conflict. Our results extend this finding to lethal violence, suicides, and homicides, implying that a government characterized by transparency and the rule of law can effectively mediate the tensions that might otherwise arise from ethnic and religious divisions.

Our analysis of the socioeconomic variables, particularly income inequality (GINI) and unemployment (UN), reveals some intriguing dynamics. While unemployment consistently shows a positive short-run association with suicides, indicating a rapid response to economic shocks, its long-run effects are less clear. More notably, our long-run findings show that a negative association exists between the Gini coefficient and suicides and homicides. This counter-intuitive result, which suggests that higher income inequality is linked to lower suicide and homicide rates, warrants further

investigation. It may indicate that the long-run effects of income inequality in the U.S. are mediated by other factors not captured in our model, or that the mechanisms linking inequality to different forms of violence are more complex than previously understood.

The short-run dynamics captured by the Error Correction Model provide additional insights. The significant positive coefficients for the differenced diversity variables (e.g., D(EF), D(EP)) indicate that a change in diversity measures can immediately influence violent behavior. This reinforces the idea that these societal characteristics are not just long-term determinants but also active catalysts for short-term fluctuations in violence. Furthermore, the varying speeds of adjustment to long-run equilibrium (39–46% for lethal violence, 31–58% for suicides, and 12–15% for homicides) suggest that each type of violence has a different underlying dynamic. This is a critical finding that has not been widely explored in the literature and suggests that homicides may be more path-dependent than suicides or lethal violence.

Conclusion and policy implications

Based on an analysis of lethal violence, suicides, and homicides from 1945 to 2023, this study demonstrates the significant and enduring impacts of ethnic and religious diversity in the United States. The findings reveal that greater societal fractionalization and polarization are consistently and positively associated with higher levels of violence. Conversely, improved democratic performance is a robust predictor of lower levels of violence. This research underscores that while diversity may present complex societal dynamics, robust democratic governance serves as a critical mitigating factor, suggesting that strengthening democratic institutions can be a powerful tool for reducing violence in diverse societies.

A critical finding of this study is that our results do not suggest that ethnic and religious diversity are inherently detrimental. Instead, they highlight that the societal tensions and violence associated with diversity are exacerbated by underlying issues of economic inequality and a lack of effective, inclusive governance. Therefore, the policy implications of this research are not to discourage diversity, but rather to promote policies that build a more cohesive and equitable society. This can be achieved by strengthening democratic institutions to mediate tensions, addressing economic disparities to reduce feelings of relative deprivation, and fostering social cohesion to build bridges between diverse communities. By focusing on these structural factors, policymakers can create environments where diverse populations can thrive without the destructive consequences of violence.

Limitations

Despite its significant findings, this study has several limitations that should be noted. First, our analysis relies on macro-level, aggregate data for the United States. While this provides a broad overview of long-term trends, it may not capture the specific, localized dynamics of violence within individual communities or states. As such, the

findings may obscure important nuances that could be uncovered through more granular, disaggregated data. Second, although our ARDL models establish strong long-run and short-run relationships, they do not definitively prove causality. The complex nature of social and economic variables makes it difficult to completely rule out the influence of unobserved or omitted variables that could be affecting both diversity and violence. Finally, this study is limited to the context of the United States. While our findings are highly relevant to the U.S. experience, they may not be generalizable to other nations with different political systems, economic structures, or histories of ethnic and religious diversity. Future research could benefit from a comparative analysis across multiple countries to determine if these relationships hold true in other contexts.

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