International Journal of Communication 20(2026), 2453-2479 1932–8036/20260005

From Words to Harm: Hate Speech and Societal Violence in U.S. Presidential Campaigns

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Political speeches are typically viewed as mobilizing democratic participation, yet research shows elite political rhetoric—particularly when it contains hate speech—may contribute to societal harm. Our study extends this line of research by investigating the association between hate speech and societal violence from a temporal perspective in the context of U.S. presidential campaigns. We examined the extent to which hate speech was associated with crime incidents across the 2 weeks following a campaign address, spanning multiple crime categories. We found that hate speech was positively and significantly associated with hate crime, property crime, crimes against society, and overall crime, but not with violent crime. These patterns suggest spillover effects of hate speech beyond hate-motivated violence. The association with hate crime emerged after a short delay, whereas associations with other crime categories were more persistent over time. Our study advances understanding of the societal impact of harmful political

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Date submitted: 2026-04-12

[1] Funding statement: The authors received no financial support for this work. Conflict of interests: The authors declare no conflicts of interest. Ethics approval: Institutional Review Board (IRB) review was not required for this study, as determined by the IRB at the University of California, Davis.

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rhetoric and has practical implications for designing interventions to counter hate speech.

Keywords: political rhetoric, hate speech, societal violence, crime, presidential campaigns

Political discourse has become increasingly disrespectful and unsubstantiated in the United States (Pew Research Center, 2019). Politicians are more likely to disengage from policy-focused debates and instead adopt aggressive language to attract public attention (Bormann et al., 2022) and mobilize their supporter base. This trend has raised concerns among scientists and the general public. Scholars argue that social media posts by political elites may fuel hatred and violence by encouraging audiences to dehumanize out-group members and minorities (Ott, 2017). Moreover, seven of 10 Americans believe aggressive language used by elected officials can inspire some individuals to commit violent acts (Pew Research Center, 2024). This study seeks to reveal the potential harm of hate speech by investigating its association with societal violence from a temporal perspective in the context of presidential campaigns.

Although several studies have documented a significant association between hate speech and hate crime (Arcila Calderón et al., 2024; Kim et al., 2022a; Müller & Schwarz, 2023), important gaps remain in understanding how hate speech may be correlated with offline criminal behavior. First, much of the existing literature links online hate speech to offline crime outcomes, a strategy that raises unresolved theoretical and inferential questions. In particular, the mechanisms through which exposure to online messages, often decontextualized and weakly embedded in local social environments, is associated with criminal acts in physical communities remain underspecified. The spatial and social distance between online expression and offline behavior makes it difficult to identify how, when, and through whom such messages are internalized and acted on.

To address this limitation, the present study focuses on hate speech delivered in offline, place-based political campaigns, where exposure occurs within shared physical and social contexts. By examining hate speech articulated during in-person political events and its association with subsequent crime incidents in the surrounding community, this study provides a more direct alignment between hate speech and local behavioral outcomes. This design not only strengthens the empirical basis for linking hate speech to societal violence but also opens clearer pathways for further research to theorize mechanisms, such as interpersonal diffusion, media amplification, and local norm shifts, that may connect elite rhetoric to real-world harm.

Second, existing research has primarily examined the relationship between hate speech and hate crime (Arcila Calderón et al., 2024; Müller & Schwarz, 2023), with limited attention to whether the effects of hate speech extend beyond targeted groups to broader patterns of criminal activity. Hate speech may alter the social climate by legitimizing hostility and eroding normative constraints against aggression (Álvarez-Benjumea & Winter, 2020; Bilewicz & Soral, 2020), processes that are not necessarily confined to violence directed at specific out-groups. Such normative erosion may have spillover effects that increase the likelihood of other forms of societal violence affecting the general public. In addition, hateful rhetoric may heighten antagonistic sentiments that can spread through social networks via emotional contagion (Stapleton & Dawkins, 2022). Such community-level arousal may amplify animosity in the local community

https://doi.org/10.65476/dfkaet24

(Drury, 2026) and lower inhibitions against aggressive behavior. Together, these dynamics highlight a critical area of inquiry. This study addresses the gap by investigating the extent to which hate speech is associated with a broader range of crime categories, such as violent crime, property crime, and crimes against society. In doing so, this research advances understanding of the scope of hate speech's societal consequences.

This study has important implications for designing interventions to counter hate speech and reduce its societal harm. By emphasizing the temporal pattern in the association between hate speech and crime incidents, the study motivates a shift away from interventions that focus on immediate containment toward strategies that consider when harmful effects are most likely to emerge. In addition, by examining multiple categories of crime rather than limiting attention to hate crime alone, this research highlights the need for targeted and mechanism-specific responses to hate speech, recognizing that different forms of harm may operate through distinct social and normative pathways. Thus, our study encourages a theoretically informed approach to countering hate speech—one that prioritizes timing and differentiation across types of societal harm.

In the following sections, we begin by reviewing the literature on the direct and indirect influences of hate speech and discussing the theoretical mechanisms underlying the association between hate speech and societal violence. We then present our computational analyses examining the relationship between hate speech and various categories of crime, with particular attention to temporal dynamics. Finally, we discuss the findings and their implications.

Literature Review

Direct and Indirect Influences of Hate Speech

Hate speech refers to inflammatory discourse that promotes hatred toward certain groups based on their characteristics such as race, gender, religion, sexual orientation, immigration status, and nationality (Kim et al., 2022b; Rosenfeld, 2002). The effects of hate speech can manifest through both direct and indirect mobilization in political campaigns. Direct mobilization involves interaction between politicians and voters in the dissemination of political ideas and policymaking processes (Rosenstone & Hansen, 1993). This process includes contacting supporters through rallies, mailings, phone calls, and door-to-door canvassing. Direct mobilization occurs when political leaders have strong incentives to achieve their goals (Kim, 2022). We situate our study in the context of in-person political campaigns, where hate speech from candidates is more likely to have a direct influence on rally attendees.

Furthermore, the effects of a political gathering can extend beyond the initial contact through the process of indirect mobilization (McClurg, 2004), whereby individuals are contacted by others in their social networks and indirectly exposed to political messages (Rosenstone & Hansen, 1993). Political information is transmitted through interpersonal discussions in the social environments where individuals are embedded (McKenzie, 2004). These environmental influences, mediated by citizen communication (Cho, 2011), likely affect individual behaviors (Oxendine et al., 2007). As a result, intense campaign efforts may alter the

information environment by increasing information seeking and interpersonal political discussion (Cho, 2011), thereby facilitating the spread of hate speech.

To summarize, the logic of direct and indirect mobilization can apply to hate speech in political campaigns. Hateful rhetoric delivered at campaign rallies reaches local communities not only through direct exposure but also through interpersonal interactions, social media communication, and media coverage. Information is transmitted through family and social networks (Sinclair, 2012), while local news further amplifies campaign messages to broader audiences (Zaller, 1992). As these exclusionary narratives saturate the local information environment, they reinforce political cues beyond those directly exposed and may become associated with political action.

Hate Speech and Societal Violence

Through both direct and indirect mechanisms, hate speech may be associated with societal violence (Ntontis et al., 2024; Wahlström et al., 2021), as reflected in crime rates (Ferguson, 2015). A frequently discussed example involves candidate speeches and campaign messages during election periods. Some studies have reported short-term increases in hate crimes targeting certain groups after political leaders deliver messages perceived as discriminatory toward those groups (e.g., Müller & Schwarz, 2023). More broadly, research using law enforcement data and media reports has documented increases in reported hate crimes following major political events, including national elections (Edwards & Rushin, 2018; Warren-Gordon & Rhineberger, 2021). Additionally, the relationship between hate speech and violence extends beyond hate crime. Prior work reveals that violent political rhetoric may correlate with an increase in mass shootings (Nugent et al., 2022).

Comparative scholarship suggests the relationship between hate speech and societal violence may not be limited to the United States. In Hungary, anti-immigration campaigns have been used by political elites to construct migrants as threats to national security and collective identity (Bocskor, 2018). In Africa, the 1994 Rwandan genocide was linked to inflammatory broadcasts from radio stations (Yanagizawa-Drott, 2014). Studies of populist discourse in India and Pakistan likewise link anti-elite messaging on social media to the spread of hate speech (Hussain et al., 2024), while analyses of a leader's rhetoric in the Philippines show how violent discourse helped cultivate a strongman political persona (De Chavez & Pacheco, 2020). Together, these international cases suggest political leaders and other influential communicators can diffuse exclusionary messages, which may in turn be associated with violence and political unrest.

The theoretical processes underlying the relationship between hate speech and societal violence are complex and multifaceted. In particular, hate speech legitimizes perceived out-group threats, which may be associated with increased violence against out-group members (Piatkowska & Stults, 2022). Hateful rhetoric often portrays minorities as dangerous and inferior, framing them as a threat to the dominant group (Perry, 2001). Social psychological theories shed light on the mechanisms underlying intergroup conflict. The integrated threat theory (Stephan et al., 2000) posits that a growing minority population threatens White Americans by competing for political and economic power with the dominant group (i.e., realistic threat). Additionally, the cultural values brought by minority groups challenge the worldviews and traditions upheld by the majority (i.e., symbolic threat). As a result, these threats

https://doi.org/10.65476/dfkaet24

encourage prejudice and aggression against out-groups. The theory is supported by empirical evidence. For instance, research shows that when a predominantly White neighborhood experiences an influx of minority members, White individuals express heightened fear and biased attitudes toward the new residents (Major et al., 2018). Moreover, racial demographic shifts are linked to an increase in hate crime against minorities in a community (Lyons, 2007).

Furthermore, hate speech tends to amplify group-status threats posed by out-groups, intensifying intergroup conflict and hostility. According to social identity theory (Tajfel & Turner, 1986), when members of the dominant group perceive their group's influence and position as declining—a phenomenon known as group-status threat—they often attribute this loss to the presence of rival groups. The intrinsic need to maintain the group's status quo motivates members to distance themselves from rival groups and develop discriminatory attitudes toward out-groups (Major et al., 2018).

Existing scholarship has also proposed frameworks for understanding when hate speech is likely associated with physical violence. The dangerous speech framework (Benesch, 2023) and the Rabat Plan of Action (Febryani, 2026) both emphasize that the relationship between speech and violence depends not only on message content but also on contextual factors, including the speaker, intent, audience, extent of dissemination, and likelihood of harm. These frameworks provide important theoretical context for understanding the association between hate speech and societal violence.

Taken together, these factors show hate speech has the potential to mobilize societal violence, particularly during political campaigns. By amplifying perceived threats from out-groups, it may reinforce hostile attitudes and heighten anger among members of the dominant group, thereby increasing the risk of violence against minorities. Therefore, hate speech may be associated with higher levels of hate crime, defined as "criminal offenses that were motivated, in whole or in part, by the offender's bias against the victim's race, ethnicity, ancestry, gender, gender identity, religion, disability, or sexual orientation, and that were committed against persons, property, or society" (Federal Bureau of Investigation [FBI], n.d., p. 7). Based on this reasoning, we propose the following hypothesis:

H1: Hate speech is positively associated with the number of hate crime incidents.

The effects of hate speech may extend beyond its targeted groups, contributing to broader patterns of violence that are not limited to hate-motivated aggression. Hate speech can shift the social climate by legitimizing aggression, signaling that hostility toward certain groups is acceptable and lowering normative and moral inhibitions against criminal behavior. Once aggression is normalized, it may generalize into everyday violence, such as violent crime. In addition, hate speech may sort people into groups, encouraging individuals to interpret ambiguous situations through hostile lenses and to act collectively, thereby increasing the risk of property crime, such as burglary and vandalism, which often accompany group-based disturbances. Beyond crime with direct victims, hate speech may also erode social norms, defined as shared rules, beliefs, and behaviors in a close or broad social environment (Cialdini & Trost, 1998). This process may contribute to crimes against society—offenses that violate laws regulating public order, morals, and safety, such as drug and weapon law violations. Although the effects of hate speech on a broad range of criminal activity are theoretically grounded, empirical evidence

examining such spillover effects remains scarce (Nugent & Khalil, 2024; Piazza, 2020). Therefore, we propose the following research question:

RQ1: How is hate speech associated with violent crime (RQ1a), property crime (RQ1b), crimes against society (RQ1c), and overall crime incidents (RQ1d)?

While the crime categories examined here contain diverse offenses, they can be distinguished according to the primary target of the offense and the type of harm involved. Violent crime is directed primarily at persons and represents a threat to bodily safety, whereas property crime is directed at property or ownership and threatens material security. Hate crime involves an individual victim, but the victim is targeted because of their group identity. Its harm may extend beyond the immediate victim by communicating hostility toward the social group to which they belong. Crimes against society differ from these categories because they do not necessarily involve an identifiable individual victim. Instead, they are defined as violations of public order, regulatory rules, or collectively established social norms.

Although previous studies have documented associations between hate speech and societal violence (Edwards & Rushin, 2018; Müller & Schwarz, 2023; Warren-Gordon & Rhineberger, 2021), little research has systematically examined the temporal dynamics of these associations. As a result, existing literature provides limited insight into when these associations emerge or whether their temporal patterns differ across crime categories. To address this gap, we investigate how the associations between hate speech and crime vary across different temporal windows. Examining these temporal dynamics provides a more nuanced understanding of how hate speech is associated with societal violence and may help distinguish temporal patterns of association across different categories of crime. Accordingly, we propose the following research question:

RQ2: How do the associations between hate speech and hate crime (RQ2a), violent crime (RQ2b), property crime (RQ2c), crimes against society (RQ2d), and overall crime incidents (RQ2e) vary over time?

Method

Data

This study uses data sets on hate speech and crime. First, we focus on hate speech in presidential campaigns from both the Republican and Democratic Parties. Campaign speeches were collected from the American Presidency Project, hosted by UC Santa Barbara (https://www.presidency.ucsb.edu/). This nonpartisan database has been widely utilized in academic research (Gonzalez, 2019; Khajavi et al., 2020). Each speech document includes the date, location, speaker, and transcript, allowing us to identify the county where the speech took place. We collected speeches delivered by presidential candidates from the two major parties during the 2016, 2020, and 2024 election years. Because of COVID-19, some campaign events in 2020 were moved online; however, we included only in-person campaign addresses. Based on these criteria, 315 campaign speeches were collected, of which 11 were excluded because of missing location information, leaving 304 speeches for analysis. Specifically, the data set includes 116 speeches delivered by Donald

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Trump and Hillary Clinton in 2016; 59 by Donald Trump and Joseph Biden in 2020; and 129 by Donald Trump, Joseph Biden, and Kamala Harris in 2024.

Second, crime data came from the FBI. Specifically, we collected the Hate Crime Statistics data set from the FBI's Uniform Crime Reporting program. The data set includes the incident date, offense type (e.g., intimidation, assault), bias description (e.g., anti-LGBTQI+), offender race, and numbers of victims and offenders. Each incident is reported by a law enforcement agency identified by a unique originating agency identifier (ORI). Using agency locations, we aggregated hate crime data to the county level. We also retrieved data on violent crime, property crime, and crimes against society from the National Incident-Based Reporting System, also administered by the FBI. Each incident contains similar information, including the incident date, offense type, and agency ORI.

Measurements

Hate Speech

Hate speech was operationalized as the average toxicity score across all sentences in a campaign address delivered in a county. Toxicity scores were obtained using a computational text analysis approach. Specifically, we employed the Perspective API hate speech classifier (https://developers.perspectiveapi.com/s/about-the-api?language=en_US), a widely used tool in social science research for identifying hateful language (Gervais et al., 2025; Lees et al., 2022). For example, Okpala et al. (2025) employed Perspective API's toxicity classifier to detect offensive content in online discourse. The classifier was trained on diverse textual sources, including comments from Wikipedia and *The New York Times*, and produces probabilistic scores ranging from zero to one across six attributes, comprising toxicity, severe toxicity, identity attack, insult, profanity, and threat, with higher values indicating greater severity. Although recent large language models have shown promise for text classification, we employed Perspective API because it provides a standardized, validated, and reproducible measure of hostile rhetoric that facilitates comparison with prior research.

Conceptually, we clarified the relationship between toxicity and hate speech. According to Perspective API (n.d.-b), toxicity refers to "a rude, disrespectful, or unreasonable comment," reflecting the overall hostile nature of communication rather than only specific forms of abuse (p. 5). Toxicity and hate speech are conceptually related because both involve hostile and inflammatory communication. Therefore, we operationalized toxicity as an indicator of the hostile rhetorical climate through which elite hate speech is expressed.

This conceptualization also helps explain why we selected the toxicity attribute rather than narrower Perspective API attributes, such as identity attack or insult. These attributes are designed to detect specific forms of abusive language, whereas elite political speeches typically communicate hostility through indirect, coded, or implicit rhetoric that may not be captured by these narrower classifiers. Additionally, there is no universally agreed-on threshold for classifying hate speech using automated tools. While Perspective API recommends relatively high cutoff values (e.g., 0.7–0.9) for studying harassment (Perspective API, n.d.-a), such thresholds risk neglecting subtle and indirect forms of hate speech, which are particularly common in

political speeches (Okpala et al., 2025; Strathern & Pfeffer, 2022). Applying a binary cutoff in this context may therefore underestimate the prevalence and influence of elite-level hateful rhetoric.

Accordingly, we operationalized hate speech as a continuous measure, calculated as the average toxicity score of all sentences in a campaign address. This approach preserves variation in the intensity of hateful rhetoric and captures the overall rhetorical climate of political speeches rather than emphasizing a small number of extreme statements. By aggregating across all sentences, our measure reflects the saturation of hateful language to which local audiences may be exposed.

Societal Violence

Societal violence was measured by crime incidents across different categories, including hate crime, violent crime, property crime, crimes against society, and overall crime. Our primary measure of violence was the total daily number of crime incidents. Specifically, we calculated the number of crime incidents in a county on the day a presidential candidate held a campaign rally in that county. This calculation method was applied to both hate crime and overall crime. In addition, violent crime comprises four offenses: murder and nonnegligent manslaughter, rape, robbery, and aggravated assault (FBI, 2018). Property crime includes burglary, larceny-theft, motor vehicle theft, and arson (FBI, 2018). Crimes against society encompass drug/narcotic violations; drug equipment violations; betting/wagering; operating, promoting, or assisting gambling; gambling equipment violations; sports tampering; pornography or obscene material offenses; prostitution; assisting or promoting prostitution; and weapon law violations (FBI, 2020). We aggregated incidents involving the relevant offenses to construct measures of violent crime, property crime, and crimes against society.

Control Variables

County demographics were included as control variables, such as population size, household median income, White ratio, gender ratio, and college attainment. White ratio was calculated as the number of White residents divided by population. Gender ratio was calculated as the number of males divided by population. College attainment was calculated as the percentage of the population that held a college degree or above. Population and household median income were log-transformed to reduce the impact of large values on the regression estimates.

Additionally, we controlled for election-year effects using dummy variables for 2020 and 2024 (with 2016 as the reference category) to account for year-specific factors that may influence both campaign rhetoric and crime patterns. Prior research indicates that crime rates exhibit seasonal variation, with higher levels typically observed during the summer months (McDowall et al., 2012; Shiode et al., 2023). Accordingly, we included temporal controls in the form of month fixed effects to account for seasonality in crime. We also controlled for campaign competitiveness, operationalized as the county's average absolute difference between Republican and Democratic vote shares across the 2016, 2020, and 2024 presidential elections. Smaller vote-share gaps indicate more politically competitive counties, which may attract greater campaign activity and increase political tensions.

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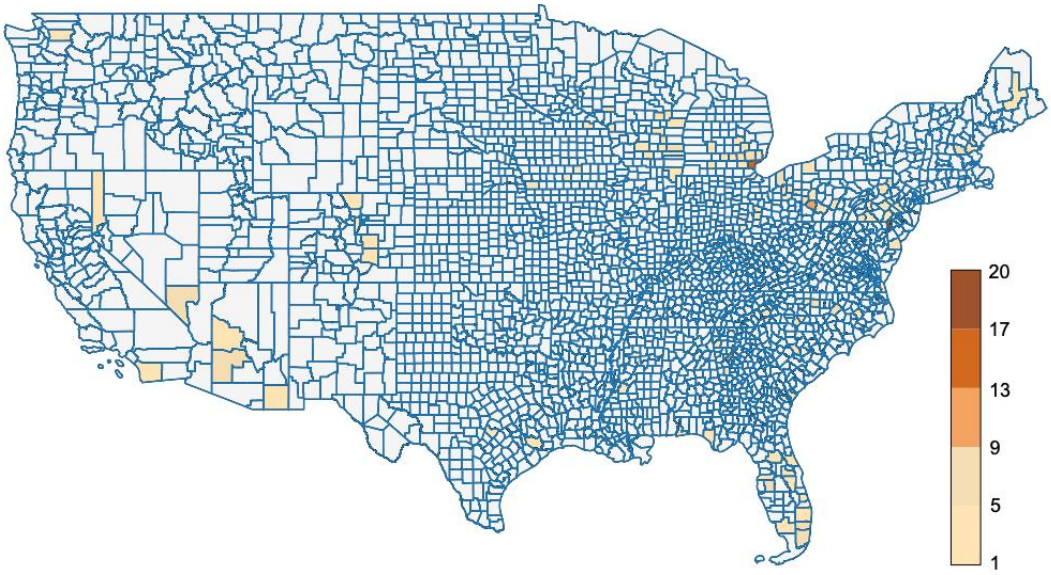
a.



b.

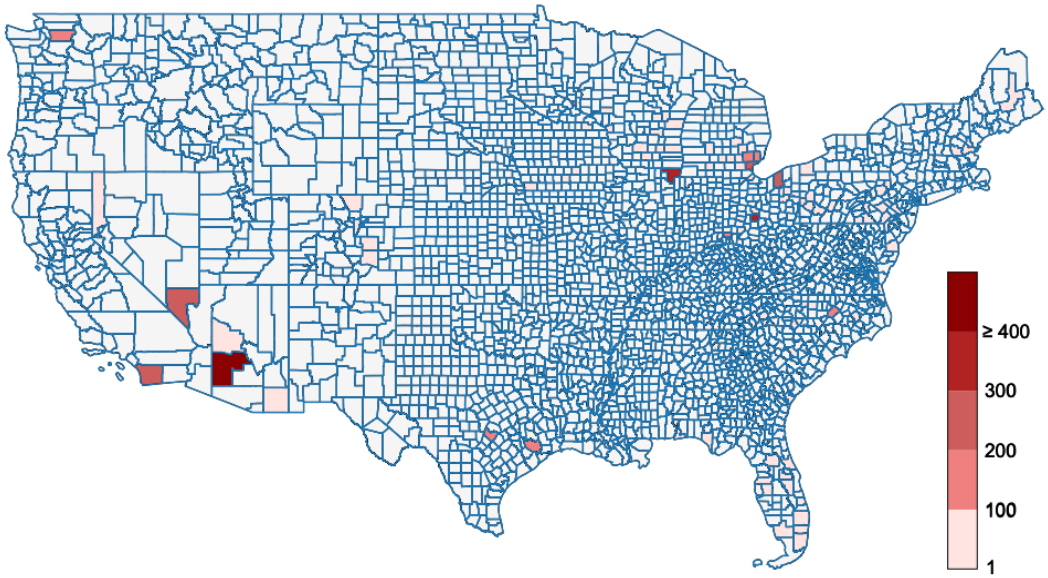
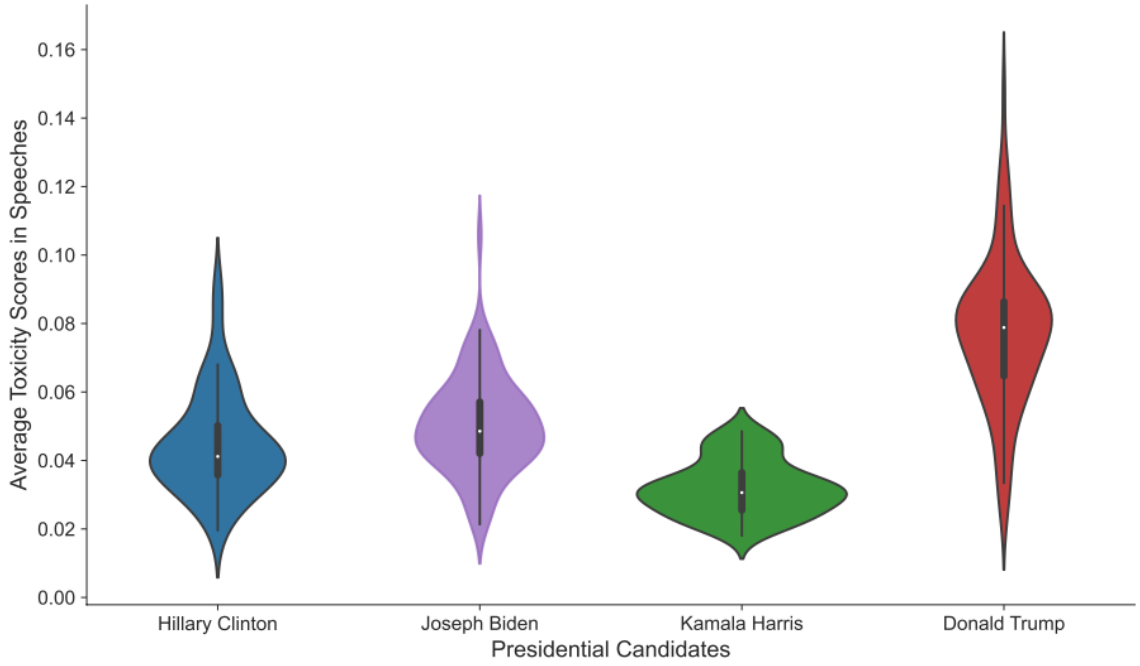


Figure 1. Distribution of political campaign speeches and hate crime across counties in three election years (U.S. Census Bureau, 2020). a. The frequency of campaign speeches held by counties. b. The total number of hate crime incidents in counties.

Figure 1a illustrates the geographic distribution of U.S. counties that hosted political campaign speeches in the 2016, 2020, and 2024 election cycles. Counties are shaded according to the frequency of speeches, with darker colors indicating higher concentrations of campaign activity, while counties shown in white did not host any campaign speeches during these election cycles. In total, speeches were delivered in 113 counties nationwide. Counties hosting more than 10 presidential campaign speeches include Philadelphia County (Pennsylvania), New Castle County (Delaware), Wayne County (Michigan), Allegheny County (Pennsylvania), and Fulton County (Georgia). A complete list of counties and their corresponding number of speeches is provided in the Appendix (see Table 2). Figure 1b presents the total number of reported hate crime incidents in counties that hosted campaign speeches across the same three election cycles. Counties shaded in darker colors experienced higher levels of hate crime activity, whereas lighter shades indicate fewer incidents. The figure highlights the variability in hate crime incidents across counties during election years. We note that only 108 counties are displayed in Figure 1b, as five counties did not report any hate crime incidents to the FBI.

a.



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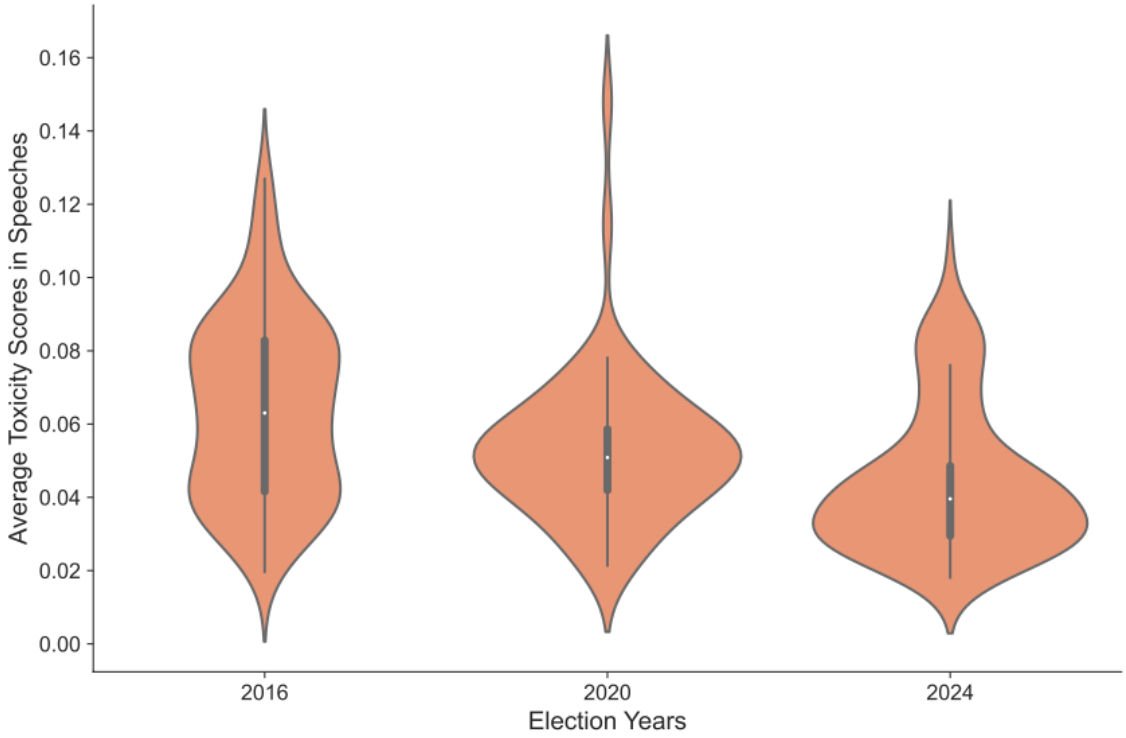

Figure 2. Distribution of average toxicity scores in political campaign speeches. a. Average toxicity scores in speeches by candidates. b. Average toxicity scores in speeches by year.

In Figure 2a, we calculated average toxicity scores for each presidential speech and showed the distributions of the scores for each candidate. Because we considered all the sentences in a speech during calculations, the average score was relatively low, but the comparison among the candidates was more meaningful than the absolute values. As shown in the figure, Donald Trump was more likely to use toxic language in his addresses compared with the remaining candidates, consistent with what previous research observed (Ott, 2017). In Figure 2b, we aggregated the campaign speeches by year and presented the distributions. The average toxicity score for speeches declines over the years, suggesting a downward trend about the use of toxic language in political campaigns.

Analytical Strategy

To test our hypothesis and address the research question, we employed Poisson regression to model the number of crime incidents occurring in a county as a function of the average toxicity scores of campaign speeches delivered in that same county. This modeling approach is appropriate given that the dependent variable is count data with nonnegative values (Hampton et al., 2011). Although negative binomial regression is also commonly used for count outcomes, likelihood ratio tests indicated

little evidence of overdispersion (Feinberg et al., 2022); therefore, Poisson regression was preferred in our analyses.

We are interested in examining both the temporal pattern of hate speech effects and cumulative effects across a 14-day period (King & Sutton, 2013). To this end, we constructed a county-day panel in which each observation represents hate speech exposure for a county within a specific time frame across the three election cycles. First, we estimated the cumulative effect across the 14-day window by averaging hate speech over this period into a single measure. This specification assesses the overall association between hate speech and crime incidents. Second, we implemented a sliding window approach that groups lagged hate speech exposure into theoretically meaningful periods. Specifically, we averaged hate speech exposure over three intervals: immediate (0–3 days), short term (4–7 days), and delayed (8–14 days). This approach captures broader temporal dynamics in the association between hate speech and crime incidents, rather than relying on individual day-specific estimates that may be sensitive to noise and multicollinearity. In brief, the cumulative model assesses whether there is an overall exposure effect across the two-week period, whereas the sliding window model examines when the association tends to emerge.

Results

H1 predicts that hate speech is positively associated with the number of hate crime incidents. We tested this hypothesis using Poisson regression, with results reported in Table 1a (cumulative model) and Table 1b (sliding window model). In the cumulative specification, hate speech was averaged across the 14-day period before the observation of crime incidents. The results show that cumulative hate speech was positively and significantly associated with hate crime incidents (β = 35.15, SE = 12.72, $p < .01$), supporting H1.

RQ1 explores the extent to which hate speech is associated with violent crime (RQ1a), property crime (RQ1b), crimes against society (RQ1c), and overall crime incidents (RQ1d). Results from the cumulative model reveal heterogeneous patterns across crime categories. Hate speech was not significantly associated with violent crime (β = 7.41, SE = 4.08, $p > .05$). In contrast, cumulative hate speech was positively and significantly associated with property crime (β = 14.52, SE = 4.00, $p < .001$), crimes against society (β = 31.69, SE = 3.68, $p < .001$), and overall crime incidents (β = 17.84, SE = 3.55, $p < .001$). These findings demonstrate heterogeneous patterns of association across crime categories, with significant relationships observed for property crime, crimes against society, and overall crime incidents, but not for violent crime.

RQ2 examines how the associations between hate speech and crime vary over time. Results from the sliding window model reveal distinct temporal patterns across crime categories. Hate speech was not significantly associated with hate crime incidents (RQ2a) in either the immediate period (0–3 days; β = 0.99, SE = 7.21, $p > .05$) or the delayed window (8–14 days; β = 16.43, SE = 8.68, $p > .05$), but it exhibited a significant positive association in the short-term window (4–7 days; β = 16.31, SE = 6.51, $p < .05$). These results suggest the association between hate speech and hate crime is not immediate, but tends to emerge after a short delay. For violent crime (RQ2b), hate speech was not significantly associated with incident counts during the immediate (0–3 days: β = 1.72, SE = 2.25, $p > .05$), short term (4–7 days: β =

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2.90, *SE* = 2.19, $p > .05$), or delayed (8–14 days: $\beta = 2.76$, *SE* = 2.88, $p > .05$) windows, indicating no evidence of temporal variation.

In contrast, property crime (RQ2c) exhibited a persistent temporal pattern. Significant positive associations were observed during the immediate (0–3 days: $\beta = 4.63$, *SE* = 2.15, $p < .05$), short term (4–7 days: $\beta = 4.40$, *SE* = 2.10, $p < .05$), and delayed (8–14 days: $\beta = 5.47$, *SE* = 2.78, $p < .05$) windows. Similarly, crimes against society (RQ2d) displayed significant positive associations across all three temporal windows (0–3 days: $\beta = 6.09$, *SE* = 1.89, $p < .01$; 4–7 days: $\beta = 9.17$, *SE* = 2.00, $p < .001$; 8–14 days: $\beta = 16.34$, *SE* = 2.49, $p < .001$), indicating both immediate and sustained effects. Overall crime incidents (RQ2e) likewise showed significant positive associations during the immediate (0–3 days: $\beta = 4.88$, *SE* = 1.89, $p < .05$), short term (4–7 days: $\beta = 5.38$, *SE* = 1.89, $p < .01$), and delayed (8–14 days: $\beta = 7.56$, *SE* = 2.49, $p < .01$) windows, suggesting a persistent temporal relationship.

Across models in Tables 1a and 1b, county-level control variables exhibited statistically significant associations with crime incidents. In particular, more populous counties reported higher numbers of incidents, while socioeconomic and demographic characteristics such as income, racial composition, and education were systematically related to crime outcomes.

Table 1a. Poisson Regression Between Hate Speech and Crime Incidents (Cumulative Model).

	Hate Crime *β* (*SE*)	Violent Crime *β* (*SE*)	Property Crime *β* (*SE*)	Crime Against Society *β* (*SE*)	Overall Crime *β* (*SE*)
Intercept	−26.63***	−1.95***	−9.38***	−11.49***	−7.52***
	(1.45)	(0.43)	(0.35)	(0.33)	(0.32)
Hate speech (0–14 days)	35.15**	7.41 (4.08)	14.52***	31.69***	17.84***
	(12.72)		(4.00)	(3.68)	(3.55)
Covariates					
Population size	0.97***	0.94***	0.83***	0.71***	0.83***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Household median income	0.75***	−2.09***	−1.33***	0.00	−0.94***
	(0.15)	(0.05)	(0.04)	(0.03)	(0.03)
White ratio	−0.43**	−2.82***	−2.56***	−1.68***	−2.29***
	(0.14)	(0.04)	(0.04)	(0.03)	(0.03)
Gender ratio	5.08	30.93***	34.36***	9.64***	23.71***
	(2.80)	(0.69)	(0.60)	(0.64)	(0.59)
College attainment	−1.29**	0.25*	1.90***	−0.66***	0.69***
	(0.41)	(0.11)	(0.10)	(0.10)	(0.09)
Campaign competitiveness	1.10***	−0.21***	−0.35***	−0.99***	−0.45***
	(0.11)	(0.04)	(0.03)	(0.03)	(0.03)
Election cycle 2020	0.29***	0.72***	0.53***	0.52***	0.58***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Election cycle 2024	0.46***	1.12***	1.01***	1.02***	1.06***
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
Month fixed effects	yes	Yes	yes	yes	Yes
Number of observations	124,092	124,092	124,092	124,092	124,092
Pseudo R^2	0.16	0.48	0.50	0.36	0.52

https://doi.org/10.65476/dfkaet24

Table 1b. Poisson Regression Between Hate Speech and Crime Incidents (Sliding Window Model).

	Hate Crime	Violent Crime	Property Crime	Crime Against Society	Overall Crime
	β (*SE*)	*β* (*SE*)	*β* (*SE*)	*β* (*SE*)	*β* (*SE*)
Intercept	−26.63***	−1.95***	−9.38***	−11.49***	−7.52***
	(1.45)	(0.43)	(0.35)	(0.33)	(0.32)
Hate speech (0–3 days)	0.99 (7.21)	1.72 (2.25)	4.63* (2.15)	6.09** (1.89)	4.88* (1.89)
Hate speech (4–7 days)	16.31* (6.51)	2.90 (2.19)	4.40* (2.10)	9.17*** (2.00)	5.38** (1.89)
Hate speech (8–14 days)	16.43 (8.68)	2.76 (2.88)	5.47* (2.78)	16.34*** (2.49)	7.56** (2.49)
Covariates					
Population size	0.97***	0.94***	0.83***	0.71***	0.83***
	(0.02)	(0.01)	(0.00)	(0.00)	(0.00)
Household median income	0.75***	−2.09***	−1.33***	0.00	−0.94***
	(0.15)	(0.05)	(0.04)	(0.03)	(0.03)
White ratio	−0.43**	−2.82***	−2.56***	−1.68***	−2.29***
	(0.14)	(0.04)	(0.04)	(0.03)	(0.03)
Gender ratio	5.08	30.93***	34.36***	9.64***	23.71***
	(2.80)	(0.69)	(0.60)	(0.64)	(0.59)
College attainment	−1.29**	0.25*	1.90***	−0.66***	0.69***
	(0.41)	(0.11)	(0.10)	(0.10)	(0.09)
Campaign competitiveness	1.10***	−0.21***	−0.35***	−0.99***	−0.45***
	(0.11)	(0.04)	(0.03)	(0.03)	(0.03)
Election cycle 2020	0.29***	0.72***	0.53***	0.52***	0.58***
	(0.04)	(0.02)	(0.02)	(0.01)	(0.01)
Election cycle 2024	0.46***	1.12***	1.01***	1.02***	1.06***
	(0.04)	(0.02)	(0.01)	(0.01)	(0.01)
Month fixed effects	yes	yes	yes	yes	yes
Number of observations	124,092	124,092	124,092	124,092	124,092
Pseudo R^2	0.16	0.48	0.50	0.36	0.52

Notes.

1. Hate speech variables represent average toxicity scores of campaign speeches aggregated over specified time windows before the observation of crime incidents. For example, the immediate window (0–3 days) captures the average toxicity score from the same day to three days prior.
2. The number of observations was calculated as the number of days across the three election years multiplied by the number of counties that hosted at least one campaign speech.
3. *β* represents coefficients, and *SE* represents standard errors.
4. **p* < .05, ***p* < .01, ****p* < .001.

Discussion

In this study, we sought to examine the potential association between hate speech and societal violence in the context of U.S. presidential campaigns. Specifically, we investigated the extent to which hate speech was associated with hate crime and broader patterns of violence, including violent crime, property crime, crimes against society, and overall crime, as well as how these associations varied over time. This study contributes by shifting the focus from online hate speech to offline contexts and by highlighting the temporal dynamics of crime following hateful political rhetoric, which offers a novel perspective on how campaign language shapes real-world outcomes. In the paragraphs that follow, we discuss the primary findings and their implications, as well as limitations and directions for future research.

We found that hate speech was positively associated with the number of hate crime incidents. In particular, cumulative hate speech over a 14-day period was significantly associated with higher levels of hate crime. This finding was consistent with theoretical perspectives suggesting that hate speech can shape intergroup perceptions and legitimize hostility toward marginalized groups. Hateful rhetoric often amplifies narratives of economic and cultural threats posed by out-groups (Stephan et al., 2000), and when voiced by political elites, it may contribute to a social climate in which prejudice becomes more acceptable. In this context, individuals may become more willing to act on hostile attitudes, increasing the likelihood of hate-motivated offenses. Prior research has also documented associations between online hate speech and subsequent increases in offline hate crime (Müller & Schwarz, 2023). Extending this line of work, the present study examined hate speech delivered in in-person campaign settings and found that such rhetoric was associated with hate crime in the same local context. By assessing this relationship in offline political events, the study provides converging evidence of an association between elite hate speech and hate crime.

Similarly, cumulative hate speech over a two-week period was positively associated with property crime, crimes against society, and overall crime incidents, supporting spillover effects beyond hate-motivated offenses. Hate speech may reshape the social climate by legitimizing hostility and weakening normative constraints against aggressive behavior. When political elites disseminate hateful rhetoric, such messages may signal that exclusionary attitudes are acceptable, thereby weakening social norms that typically inhibit deviant behavior (Bilewicz & Soral, 2020). As a result, aggression may extend beyond targeted out-groups to broader forms of criminal activity, including property offenses and violations of public order. These findings extend prior literature by showing that hate speech was associated not only with hate crime but also with a wider range of societal harms. The consistent associations across multiple crime categories suggest hate speech may be associated with a broader erosion of normative boundaries, extending its societal consequences beyond intergroup conflict to more generalized forms of disorder and deviance.

Regarding the temporal dimension, our findings reveal distinct temporal patterns across crime categories. Specifically, the association between hate speech and hate crime was not immediate, but became most pronounced in the short-term window (4–7 days following the campaign), suggesting the relationship unfolded over time. One plausible explanation lies in the diffusion of hate speech through indirect mobilization processes. Political messages disseminated at campaign events can extend beyond direct audiences through interpersonal communication, social networks, and local media coverage (McClurg, 2004;

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Rosenstone & Hansen, 1993). As hateful rhetoric circulates within communities, it may reinforce perceptions of out-group threat and normalized hostile attitudes, gradually shaping behavioral responses. This diffusion process likely takes time, which may explain why the association became evident several days after the initial exposure. Rather than prompting immediate action among rally attendees, hate speech may spread and become intensified through repeated exposure and social reinforcement, increasing the likelihood of hate crime after a short delay.

In contrast to the temporal pattern observed for hate crime, the associations between hate speech and property crime, crimes against society, and overall crime were persistent across all three time intervals: the immediate (0–3 days), short term (4–7 days), and delayed (8–14 days) windows. This pattern suggests the relationship between hate speech and these broader forms of crime may be shaped by different diffusion processes than those underlying hate crime. Rather than exhibiting concentrated effects at specific time points, the more consistent associations across windows may reflect a more continuous and widespread diffusion of hate speech in communities. The absence of distinct peaks in these crime categories raises the possibility that multiple diffusion processes—such as media amplification, social network transmission, and local contextual factors—may operate simultaneously, producing more stable patterns over time rather than delayed spikes. Although these interpretations are theoretically plausible, they remain speculative and are not directly tested in the present study. Future research should therefore investigate the mechanisms through which hate speech diffuses across communities to understand its associations with multiple types of crime and their distinct temporal patterns.

Additionally, we found no evidence that hate speech was significantly associated with violent crime in either the cumulative or sliding window models. Although our theoretical framework anticipates that hate speech can spill over into multiple forms of criminal activity, this generalization appears conditional and selective. One plausible interpretation is that the spillover effects of hate speech operate primarily through processes of normative erosion rather than direct behavioral escalation. Violent crime often requires stronger situational triggers, instrumental motivations, or immediate opportunities, which may not be directly activated by exposure to hate speech alone. Unlike hate crime, which is closely tied to intergroup hostility, or crimes against society, which reflect weakened social norms, violent crime may be less responsive to shifts in the broader rhetorical environment. Moreover, the absence of significant associations for violent crime underscores the importance of disaggregating crime categories when examining the social consequences of hate speech. Aggregated or generalized measures of violence may obscure meaningful variation across offense types, potentially masking effects that operate through distinct mechanisms.

The findings of this study carry important implications for mitigating the societal harms of hate speech, particularly when disseminated by political elites. The results suggest the association between hate speech and crime is cumulative rather than confined to immediate responses. Although some associations emerged shortly after exposure, the cumulative model indicates that repeated exposure over a two-week period is also consequential. Accordingly, interventions should extend beyond real-time responses to isolated events and incorporate sustained postexposure strategies, such as countermessaging and media framing.

Furthermore, the findings reveal that the association between hate speech and crime varies across crime types. Hate speech was associated with hate crime, crimes against society, property crime, and overall crime, but not with violent crime. This pattern suggests hate speech may operate primarily through normative erosion rather than triggering all forms of criminal behavior. Accordingly, interventions should reinforce norms of tolerance and lawful conduct through community-based initiatives, including public messaging by trusted leaders and intergroup engagement efforts.

Limitations and Future Directions

Several limitations warrant discussion. First, although the analysis captures hate speech articulated during political campaigns, exposure to hate speech in a county is not empirically observed. Instead, hate speech is estimated using the toxicity of campaign speeches delivered within a county. This distinction is important because counties vary substantially in geographic size, population distribution, media environments, and social heterogeneity. Residents in the same county may experience different levels of contact with the event and its rhetoric. The absence of individual-level exposure data prevents us from identifying who encountered the rhetoric, through which channels, and to what extent. Accordingly, given the observational nature of our study design, we refrain from making causal claims. Future research should strengthen this line of inquiry by incorporating more granular exposure measures, such as survey-based indicators of hate speech exposure, to precisely map how elite hate speech reaches broader audiences.

Second, while this study is designed to assess temporal associations between hate speech and societal violence, it does not empirically test the mechanisms through which these associations may arise. We acknowledge that counties are not isolated from one another. These geographic spaces are connected through online networks, with news media and social media serving as important channels for the dissemination of campaign messages. Through these media channels, the effects of hate speech may therefore extend beyond geographic boundaries (Guo & Zhou, 2025). We encourage future research to investigate these online mediation mechanisms. Such work could help elucidate the pathways through which hate speech correlates with societal harm and provide a more comprehensive understanding of its temporal and spatial diffusion.

Third, the Perspective API produces probabilistic toxicity scores rather than definitive labels of toxicity or harmful speech. Its annotations may not capture contextual features fully, such as speaker intent, irony, or the broader political and cultural contexts in which campaign messages are delivered (Rieder & Skop, 2021). Consequently, our findings should be interpreted as patterns in classifier-assessed toxicity rather than as direct measures of authors' intentions or legal determinations of hate speech. Future research should strengthen this approach by combining automated annotation with human validation and context-sensitive qualitative analysis.

https://doi.org/10.65476/dfkaet24

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https://doi.org/10.65476/dfkaet24

Appendix

Table 2. Number of Speeches by County.

County	State	Number of Speeches
Marshall	Iowa	1
Polk	Iowa	3
Rockingham	New Hampshire	3
Washington, DC	District of Columbia	7
San Diego	California	1
Philadelphia	Pennsylvania	20
Guilford	North Carolina	5
Orange	Florida	2
Wake	North Carolina	7
Strafford	New Hampshire	1
St. Lucie	Florida	1
Broward	Florida	6
Mecklenburg	North Carolina	6
Lucas	Ohio	1
Summit	Ohio	1
Franklin	Ohio	2
Miami-Dade	Florida	5
Pueblo	Colorado	2
New York	New York	7
Cuyahoga	Ohio	5
Allegheny	Pennsylvania	10
Hillsborough	New Hampshire	6
Hillsborough	Florida	5
Forsyth	North Carolina	1
Volusia	Florida	1
Hamilton	Ohio	2
Portage	Ohio	1
Pitt	North Carolina	3
Pasco	Florida	1
Wayne	Michigan	16
Kent	Michigan	3
Richland	South Carolina	1
New Castle	Delaware	18
Macomb	Michigan	4
Osceola	Florida	1
Lackawanna	Pennsylvania	5
Manitowoc	Wisconsin	1
Cambria	Pennsylvania	2

Adams	Pennsylvania	2
Maricopa	Arizona	8
Clark	Nevada	8
Erie	Pennsylvania	3
Oakland	Michigan	6
Luzerne	Pennsylvania	3
Bucks	Pennsylvania	3
Meriwether	Georgia	1
Fulton	Georgia	9
Ramsey	Minnesota	1
Milwaukee	Wisconsin	6
Genesee	Michigan	2
Beaver	Pennsylvania	4
Manassas	Virginia	1
Delaware	Pennsylvania	4
Washoe	Nevada	3
Racine	Wisconsin	1
Dane	Wisconsin	3
Dauphin	Pennsylvania	4
Sussex	Delaware	1
Eau Claire	Wisconsin	1
Cook	Illinois	2
Liberty	Georgia	1
Chatham	Georgia	2
Cochise	Arizona	1
Fond du Lac	Wisconsin	1
La Crosse	Wisconsin	1
Brown	Wisconsin	3
Ingham	Michigan	2
Clayton	Georgia	1
Waukesha	Wisconsin	2
De Kalb	Georgia	1
Harris	Texas	2
Kalamazoo	Michigan	2
Washtenaw	Michigan	1
Saginaw	Michigan	1
Rock	Wisconsin	1
Outagamie	Wisconsin	1
Lehigh	Pennsylvania	2
Virginia Beach	Virginia	1
New Hanover	North Carolina	1
Mahoning	Ohio	1
Washington	Wisconsin	1

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Eaton	Michigan	1
Travis	Texas	1
Hinds	Mississippi	1
Snohomish	Washington	1
Clinton	Ohio	1
Escambia	Florida	1
Buncombe	North Carolina	1
Baltimore City	Maryland	1
Stark	Ohio	1
Roanoke	Virginia	1
Pottawattamie	Iowa	1
Larimer	Colorado	1
Yavapai	Arizona	1
Bay	Florida	1
Marion	Florida	1
Palm Beach	Florida	1
Penobscot	Maine	1
El Paso	Colorado	1
Delaware	Ohio	1
Henderson	North Carolina	1
Collier	Florida	1
Clark	Ohio	1
Jefferson	Colorado	1
Chester	Pennsylvania	1
Olmsted	Minnesota	1
Floyd	Georgia	1
York	Pennsylvania	1
Livingston	Michigan	1
Butler	Pennsylvania	1
Berks	Pennsylvania	1
Westmoreland	Pennsylvania	1
Cabarrus	North Carolina	1