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RESEARCH REPORT

How advocacy groups on Twitter and media coverage can drive U.S. firearm acquisition: a causal study

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Abstract

Firearm injuries are a leading cause of death in the United States, surpassing fatalities from motor vehicle crashes. Despite this significant public health risk, Americans continue to purchase firearms in large quantities. Commonly cited drivers of firearm acquisition include fear of violent crime, fear of mass shootings, and panic-buying. Additionally, advocacy groups' activity on social media may capitalize on emotions like fear and influence firearm acquisition. The simultaneous effects of these variables have not been explored in a causal framework. In this study, we aim to elucidate the causal roles of media coverage of firearm laws and regulations, media coverage of mass shootings, media coverage of violent crimes, and the Twitter activity of anti- and pro-regulation advocacy groups in short-term firearm acquisition in the United States. We generate daily time series for these variables from 2012 to 2020 and employ the PCMCI+ framework to investigate the causal structures among them simultaneously. Our results indicate that the Twitter activity of anti-regulation advocacy groups directly drives firearm acquisitions. We also find that media coverage of firearm laws and regulations and media coverage of violent crimes influence firearm acquisition. Although media coverage of mass shootings and online activity of pro-regulation organizations are potential drivers of firearm acquisition, in the short term, only the lobbying efforts of anti-regulation organizations on social media and specific media coverage appear to influence individuals' decisions to purchase firearms.

Key words: Causal inference, firearm acquisition, firearm violence, mass media, PCMCI+, social media.

Significance statement

Understanding the drivers of firearm acquisition is essential for addressing firearm-related harms without infringing on citizens' rights. Using a causal inference framework with a daily resolution, we show that short-term firearm purchases in the United States can be primarily influenced by the Twitter activity of anti-regulation advocacy groups, media coverage of firearm laws, and media coverage of violent crimes. The results suggest that activity of advocacy groups on social media and certain media narratives can directly impact firearm acquisition, offering valuable insights for policymakers and public health initiatives aimed at reducing firearm injuries.

Introduction

Firearm violence is a major public health concern in the United States (US), where the incidence of deaths by firearms is steadily increasing. In the 20 years between 2001 and 2020, nearly 680,000 people died of firearm-related violence in the country [1]. While in 2001, nearly 30,000 people died by firearms, by 2017, this figure reached almost 40,000, averaging

109 deaths per day and surmounting the number of deaths due to motor vehicle accidents [2]. Firearm violence and injury have been strongly associated with accessibility to the agent causing the harm: firearms. Several studies showed that states with greater firearm ownership experience greater rates of suicides, homicides, and aggravated assaults with firearms [3, 4, 5, 6, 7]. Despite the evidence of their harm, many Americans continue to purchase firearms in large amounts. In fact, in addition to the risks imposed, firearm ownership is central to American culture and identity and offers citizens a multitude of benefits including physical activity, social interactions, stronger familial ties, and a connection to nature [8, 9, 10, 11]. Thus, to reconcile American citizens' wishes to own firearms with the dire need to mitigate the risk of firearm harms, it is important to understand the factors driving firearm acquisition.

Perhaps the most cited driver of firearm acquisition is self-protection. A 2019 study by the Pew Research Center revealed that 67% of owners purchased firearms to protect themselves [12]. Further, a poll conducted by NBC in 2018 showed that 58% of American adults believe that ubiquitous firearms would increase their communities' safety by allowing law-abiding citizens to protect themselves [13]. Research has attributed Americans' need for self-protection in part to their fear of victimization in violent crimes [8, 14, 15, 16, 17, 18, 19] and a 2016 Gallup survey showed that individuals who were victims of a crime are more likely to become firearm owners [20]. However, research that elucidates whether fear of crime definitively translates to firearm acquisition is limited. Hauser and Kleck analyzed surveys that followed up with respondents and were the first to show evidence that fear of crime materializes in firearm purchases [21]. In the same study, Hauser and Kleck also found that the act of purchasing a firearm did not reduce the fear of violent crimes among non-owners, the notion of relinquishing the weapon increased it.

Another path of victimization that deeply concerns Americans is fear of mass violence. The US is unique for its rates of mass shootings, where more such events take place than anywhere else in the world [22, 23]. Despite their relatively high pervasiveness in the US, mass shootings over the 20 years between 1999 and 2019 accounted for only 0.36% of firearm homicides [1, 24, 25]. Yet, the extensive media attention they garner leads people to believe they are more prevalent than they are in reality [26, 27]. To this effect, surveys by The Harris Poll (administered on behalf of the American Psychological Association) indicated that 79% of Americans experience stress by the possibility of a mass shooting, and 33% of them do not attend public events out of fear of a mass shooting [28]. Thus, mass shootings can induce "moral panic" [29, 30, 31], a perception of a threat that is disproportionately greater than the actual threat. Considering that mass shootings elicit an extraordinary sense of lack of personal safety among American citizens, Wallace suggested that mass shooting events lead to greater firearm acquisition [32]. Supporting this proposition, empirical evidence by [33, 34, 35, 36, 37, 38] shows that firearm sales spike following mass shootings.

Another possible driver of firearm acquisition in the US is rooted in "panic-buying." Panic-buying is a well-documented phenomenon where crowds anticipate future scarcity of a product and buy unusually large amounts of it [39]. For example, introducing a "New Coke" beverage formula in 1985 led many consumers to panic-buy the original Coke until its depletion in stores [40]. In the context of firearms, panic-buying would correspond to the rushed purchase of firearms and ammunition in anticipation of looming firearm regulation. Panic-buying of firearms was recorded in 2008 as demand for firearms surged following the election of President Barack Obama, whose political agenda included stricter firearm laws, in 2013 in New Jersey following Governor Christie's proposal to expand background checks and ban rifles, and in Maryland before the ban of semiautomatic rifles [41, 42]. Thus, it is expected that greater acquisition of firearms will be observed following the announcements of firearm regulations.

The public's perception of potential victimization and their knowledge of upcoming firearm regulations are likely shaped by the portrayal of such events on mass media [43, 44, 45, 46]. As media capitalize on the attention they attract, outlets tend to sensationalize events to draw an audience. Prior studies have shown that news reports exaggerate stories of more violent crimes, and that the amount of media coverage of such events is disproportionate to their rate of occurrence [44]. The media guide the public's perception of social problems and even serve agendas [44, 47, 48], but also drive certain behaviors [46, 49]. As such, media coverage of relevant topics could be a proxy of the public' fear of violent crimes, mass shootings, and firearm restrictions.

The three aforementioned potential drivers of firearm acquisition were studied throughout the years in correlation studies, linear regressions, or evidence-based inferences. Recently, our group investigated their media coverage in a causal framework [50]. We collected the count of mass shootings, the count of newspaper articles on shootings, the count of newspaper articles on firearm control, and the number of background checks (as a proxy for firearm purchases) in the country every month between 1999 and 2017. To quantify the interaction between each pair of the four variables, we computed transfer entropy between their time series. Transfer entropy quantifies causality in a Wiener-Granger sense as the reduction in uncertainty of the prediction of the future of a variable, given knowledge about its history and the history of another variable [51]. It can effectively quantify causal links in the presence of nonlinear interactions (where the interaction is dictated by a power-law or U-shaped relationship) and multiple time delays [52, 53], and also in instances where counterfactual measurements are absent [54]. Among all pairwise interactions we inspected, our results indicated that only two links are causal: the one from mass shootings to media coverage of shootings and the one from media coverage of firearm control to background checks. These findings were further supported by subsequent analyses [55, 56].

The results raise two questions. First, it is possible that the links from mass shootings to background checks and from media coverage of shootings to background checks were not found because the process between those variables takes place in a shorter period of time than the monthly resolution of data. That is, people are exposed to breaking news on violent crimes and mass shootings and prompted to purchase firearms within days, not months. Second, it is tenable that replacing the time series of mass shootings with a time series of media coverage of mass shootings would better reflect the public's perception of danger from these events. In the present study, we expand on the analysis in Porfiri et al. [50] and perform it with daily data so that we might capture processes that take place on a shorter time scale of days. Such an analysis could not have been conducted before, as the Federal Bureau of Investigation (FBI) only made daily background check data available in 2021.

In addition to these innovations, this study offers insight into another potential driver of firearm acquisition: the activity of interest groups on social media. American interest groups exist for a wide range of societal, economic, and environmental causes, including public healthcare, abortion, immigration reforms, and climate change [57]. There are two opposing interest groups in the domain of firearms: anti-regulation organizations and pro-regulation organizations. Firearm enthusiasts contend that the US Constitution protects the right to own a firearm. In contrast, proponents of firearm control are often prompted by firearm-related tragedies to advance legislation that restricts access to firearms. Both interest groups are well-represented at the state and federal levels of government.With the rise of social media, Facebook, Twitter (now X), and YouTube have become substantial platforms for interest groups to express their agendas through "outside lobbying" [58]. Outside lobbying refers to interest groups' attempts to mobilize citizens rather than policymakers to influence public officials [58]. Pro- and anti-regulation organizations also use these platforms to promote their agendas among citizens, however, research on the topic suggests that these organizations adopt different strategies. Auger assessed the use of social media by pro- and anti-regulation nonprofits and found that while both engaged with their communities and expressed gratitude toward their stakeholders, the former are more likely to emphasize conflict on their social media channels while the latter publish content about politics and legislation [59]. In agreement with this finding, Merry showed that the timing of content release differs among the interest groups, whereby pro-regulation organizations' activity peaks following mass shooting events and emphasizes victims and heroes [60]. In contrast, anti-regulation organizations published less content around these events and focused on legislative actions. In both cases, as interest groups aim to gain traction among their followers, they likely target identity issues and emotions [61].

The strategic use of social media by interest groups not only shapes public perception but also contributes to broader societal trends, such as political polarization. Studies have shown that social media platforms amplify partisan sorting, where individuals increasingly engage with extreme rather than moderate views, deepening divisions between opposing political groups [62]. This process of partisan sorting is influenced by users' tendency to form social ties based on shared partisanship [63]. Furthermore, exposure to opposing views on social media, rather than reducing polarization, can increase political polarization, further entrenching the opposing stances of these interest groups [64]. Subsequent studies also highlight that political segregation on social media is driven not only by homophily but by acrophily, a preference for engaging with more politically extreme users rather than moderate, which can amplify inter-group antagonism [65].

While the literature on the modus operandi of anti- and pro-regulation organizations is vast, studies on their influence on public behavior are limited, and causal analysis in this domain is scarce. This study is the first to analyze the role of both interest groups as potential drivers of firearm acquisition. Given that this study examines links between six variables that are likely interacting (firearm acquisition, activities of anti- and pro-regulation interest groups, and media coverage of firearm laws and regulation, mass shootings, and violent crime), transfer entropy is not an ideal approach for this endeavor due to the curse of dimensionality [66, 67]. Thus, we employ PCMCI+, a framework for discovering links within a graph [68]. Building on the PC algorithm [69], it was designed for high-dimensional data sets. PCMCI+ successfully captures contemporaneous interactions and delayed dependencies.

Here, we investigate the role of mass and social media in driving firearm acquisition within a time scale of days. We report results for PCMCI+, applied to five potential drivers of firearm acquisition: media reports on violent crimes, media reports on mass shootings, media reports on firearm regulations, and activities of both anti- and pro-regulation organizations on social media.

Methods

We collected daily data about six variables, summarized in Table 1: i) media coverage of firearm laws and regulation, ii) media coverage of mass shootings, iii) media coverage of violent crime, iv) Twitter posts (colloquially known as "tweets") by anti-regulation organizations, v) tweets by pro-regulation organizations, and vi) background checks.

For the first three variables (i-iii), media coverage was measured as the number of newspaper articles published on a topic collected from the ProQuest search engine (access provided by Georgia State University libraries) [70]. Numbers were obtained using a procedure identical to the one reported in Porfiri et al. [50]. Beginning with media coverage of firearm laws and regulations (variable i), we searched for the term "firearm laws" and included "firearm laws and regulations" in the Subject filter. We set the Source Type to "Newspapers" and specified the following ten Publication Titles: Arizona Republic, Chicago Tribune, Denver Post, Houston Chronicle, Los Angeles Times, New York Times, Orlando Sentinel, St. Louis Post-Dispatch, Times-Picayune, and Wall Street Journal. These ten daily news outlets represent liberal and conservative readerships across the US regions [71, 72].

To quantify media coverage of mass shootings (variable ii), we performed a similar search, querying newspaper articles about "shootings." Within the Subject filter, we included "shootings" or "mass murder" and excluded "firearm laws and regulations." Finally, we used the term "violent crime" when searching for media coverage of violent crime (variable iii). The same Source Type and Publication Titles were specified in both searches. The results for each query were exported to a comma-separated values (csv) document and aggregated by date to obtain the daily number of articles. The queries to reproduce these time series are available in Supplementary Table 1. A Venn diagram in Supplementary Figure 1 shows that the time series of media coverage are largely independent and do not share a large proportion of articles among themselves. To quantify the activity of pro- and anti-regulation organizations on social media, we turned to Twitter (now known as X). Twitter is a popular micro-blogging platform where account holders can publish textual content with up to 280 characters, known as tweets. Twitter is commonly used by individuals and organizations [73], with affinity to firearms and otherwise [74, 75], who tend to post tweets in response to current events in real-time [76, 77]. Until its recent rebranding as X, Twitter has allowed the scraping of tweets with highly granular time stamps and, therefore, was considered by social scientists as a "thermometer" of public discourse [78, 79, 80]. To select the most influential organizations, we queried Social Bearing [81], an analytical tool dedicated to Twitter that stores the number of followers for each account. We identified the accounts that advocate for or against firearm regulation by searching for those that mention the keyword "gun" the most (a feature offered by Social Bearing). We sorted the returned accounts by follower count in descending order and visually inspected

Table 1. A summary of the data collected in this study.

Variable	Source	Total counts
Media coverage of firearm laws and regulation	ProQuest	10.4k
Media coverage of mass shootings	ProQuest	18.3k
Media coverage of violent crime	ProQuest	20.5k
Tweets by anti-regulation organizations	Twitter (X)	155.4k
Tweets by pro-regulation organizations	Twitter (X)	238.5k
Background checks	FBI National Instant Criminal Background Check System	192,170k

their Biographies. Our selection of accounts was limited to those corresponding to firearm control organizations. That is, we excluded accounts for individual persons, organizations that address other issues related to guns, and organizations that did not have official statements regarding firearm regulation. We then categorized the top accounts by stance (anti- or pro-regulation) based on the account biography, whether it was promoting or discouraging firearm regulation. We selected the most followed accounts for anti-regulation organizations with over $5,000$ subscribers [59, 82]. Organizations like the National Rifle Association had multiple accounts, one nationwide and a few dedicated to local chapters. We selected the principal with the largest geographical and social coverage if multiple accounts were returned. Overall, nine anti-regulation accounts were included in the study. To mirror this selection, we picked the most-followed accounts of pro-regulation organizations, again thresholding at $5,000$ followers, yielding 11 organizations. In total, 20 organizations were included in this study.

To generate a time series for each interest group's activity on social media, we collected the number of posts each published. Specifically, we searched for posts containing the keyword "gun" by each organizational account using the "Counts" endpoint of the Twitter Academic Research API v2 [83]. All Twitter data were collected between February 2, 2022 and February 26, 2022. The daily number of background checks performed across the US was obtained from the FBI's National Instant Criminal Background Check System (NICS) [84]. Although background checks are not a direct measure of firearm purchases [85], they are commonly used as a proxy in the absence of a national registry [32, 50, 56, 86]. For all variables, the time series began in January 2012 when Twitter saw a surge in registered users [87]. To avoid anomalies related to the COVID-19 pandemic [88, 89, 90], the time series was truncated on January 1, 2020. As such, we generated six time series (one for each variable), each containing 2923 daily counts between January 1, 2012, and January 1, 2020.

All time series were seasonally adjusted and detrended using the forecast package on R (version 8.15; [91]). Seasonal adjustment was applied for periods of $1, 2, 3, 5, 7, 30, 31$, $365.25/12$, and 365.25 days. Subsequently, the treated time series were tested for the presence of trends using both the Augmented Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests [92, 93].

We performed causal analysis on the detrended and deseasonalized time series using PCMCI+ with the software package Tigramite [68]. PCMCI+ begins with a complete graph G, where each node X_{t_n} represents the time series of a variable at a certain time delay. The subscript $n \in (1, 2, \dots, N)$ corresponds to a variable, and the superscript $t \in (T, T-1, \dots, T-\tau)$ corresponds to a delay of the variable such that N is the total number of variables, T is the entire time series length, and $\tau \geq 0$ is the maximum delay tested for in the algorithm. The algorithm considers all specified delays applied on all variables simultaneously, thereby controlling for autocorrelations within each time series [68].

The algorithm is based on a variant of the PC algorithm [69] and the concept of momentary conditional independence (MCI) inspired by the information-theoretic measure of momentary information transfer [94]. The skeleton is discovered by heuristically testing pairwise independence between variables and later independence between variables conditioning on a set of the parents that are updated in each iteration of the algorithm. Once the skeleton of the time series graph convergences, links are oriented based on time delays for time dependencies, and based on deterministic rules for contemporaneous links; that is, if a link exists between $X^i_{t_1}$ and $X^j_{t_2}$, the orientation of the link between i and j is posed based on the difference between t_1 and t_2 ($i \to j$ if $t_1 < t_2$ and $j \to i$ if $t_2 < t_1$). For $t_1 = t_2$ deterministic rules based on Pearl's causality are applied to determine the orientation [95]. Finally, during the momentary conditional independent phase, a link is established if and only if the variables are not independent, given the set of the parents of both the sink and the source variables from the skeleton graph.

When applying the PCMCI+ algorithm, we specified possible delays of $\tau = 0, 1, 2, 3, 4, 5, 6$ and 7 days, and designated partial correlation ρ as the measure of conditional dependence between pairs of variables. The sign of ρ was used to determine whether an association is positive (both variables increase/decrease together) or negative (one variable increases while the other decreases).

Results

Complete time series were collected for all six variables (Figure 1). Media coverage of firearm laws and regulations contained a total of $10,431$ articles, with a notable activity following the Sandy Hook school shooting on December 12, 2012, reaching a peak of 51 articles in January a month later (Figure 1-a). Peaks were also observed following the San Bernardino, Orlando, Las Vegas, Parkland, and El Paso shootings. Media coverage of mass shootings resulted in a larger total of $18,338$ articles, with a peak value of 53 articles observed on July 9, 2016, 27 days after the Orlando shooting (Figure 1-b). In this time series, multiple peaks could be associated with mass shootings: all those highlighted in blue in Figure 1-b, as well as the DC Navy Yard shooting on September 16, 2013, Isla Vista mass murder on May 23, 2015, and the Congressional Baseball Shooting on June 14, 2017. Finally, media coverage of violent crimes contained a total of $20,511$ articles, with a peak of 27 articles recorded on September 30, 2016 (Figure 1-c). Peaks in this time series were not so clearly associated with major mass shooting events. A list of all the organizations used to count tweets is available in Table 2. Although anti-regulation organizations

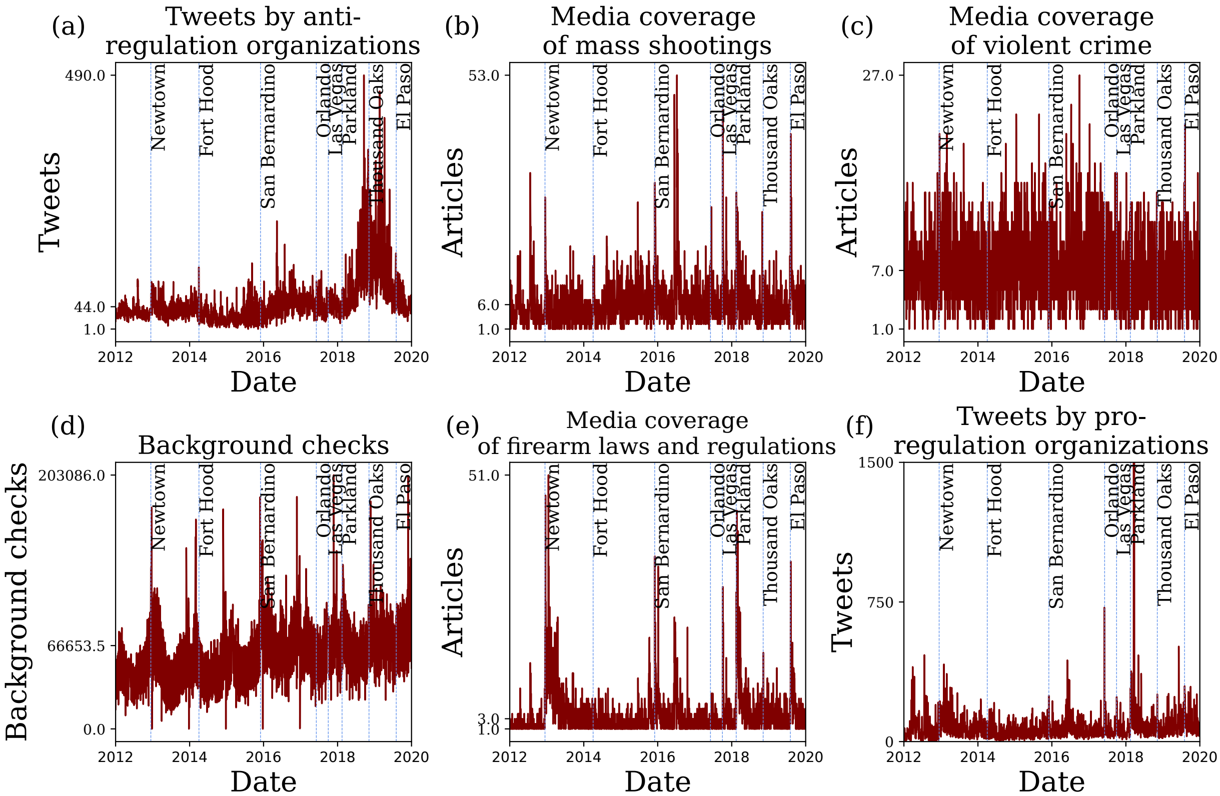

Fig. 1. Daily time series of the variables considered in the study: (a) media coverage of firearm laws and regulation, (b) media coverage of mass shootings, (c) media coverage of violent crime, (d) tweets by pro-regulation organizations, (e) tweets by anti-regulation organizations, and (f) background checks. Blue vertical lines correspond to the following deadly mass shootings (left to right): Sandy Hook (12/14/2012 in Newtown, CT), Fort Hood (4/2/2014 near Killeen, TX), Inland Regional Center (12/2/2015 in San Bernardino, CA), Pulse Nightclub (6/12/2016 in Orlando, FL), Route 91 Harvest Festival (10/1/2017 in Las Vegas, NV), Marjory Stoneman Douglas High School (2/14/2018 in Parkland, FL), Borderline Bar and Grill (11/7/2018 in Thousand Oaks, CA), Walmart (8/3/2019 in El Paso, TX).

enjoy greater followership (1.76 million subscribers versus 1.32 million), pro-regulation organizations publish many more posts. Tweets by pro-regulation organizations included $238,545$ posts, with $12,586$ published on March 24, 2018, following the Parkland shooting (Figure 1-d). Tweets by anti-regulation organizations included $155,417$ posts, with many published in the months following the Parkland shooting and a peak of 490 published on September 18, 2018 (Figure 1-e). Finally, the time series of background checks exhibited significant weekly and monthly seasonality, whereby firearm sales surged in the periods surrounding the holiday season and dipped in the summer (Figure 1-f). In this time series, too, peaks were not clearly associated with major mass shooting events.

All time series were appropriately detrended, reflected by p-values lower than 0.05 for all ADF tests (where the alternative hypothesis is stationarity) and greater than 0.1 for all KPSS tests (where the alternative hypothesis is non-stationarity; Table 3). Plots of processed time series are displayed in Supplementary Figure 2. PCMCI+ produced the graph in Figure 2, with the associated quantities summarized in Table 4. Overall, 15 links were identified in the analysis: two unorientable contemporaneous links, two orientable contemporaneous links, and 10 orientable links.

The two unorientable contemporaneous links connected the node of media coverage of firearm laws and regulations with the nodes of media coverage of mass shootings and background checks. The two orientable contemporaneous, along with two non-contemporaneous links, interconnected the nodes of media coverage. Link a extended from media coverage of mass shooting to media coverage of firearm laws and regulations, at a delay of one day ($p < 0.001$). Contemporaneous link b was directed from media coverage of firearm laws and regulations to media coverage of violent crimes ($p < 0.001$). Lasty, links c and d connected media coverage of mass shootings and media coverage of violent crime in opposing directions. While c represented a link from the former to the latter with a delay of one day ($p = 0.001$), d represented a contemporaneous link from the latter to the former ($p = 0.001$). All four links consisted of positive associations ($\rho = 0.094$, 0.100, 0.083, and 0.071 for links a, b, c, and d, respectively).

Four links reflected the associations of tweets by interest groups. Tweets by pro-regulation organizations were only associated with media coverage of firearm laws and regulations (link e), where the interaction was directed from the latter to the former ($p < 0.001$) and represented a negative association ($\rho = -0.069$). Tweets by anti-regulation organizations were associated with media coverage of violent crime and background checks. One positive link (labeled g) was directed towards media coverage of violent crime with a two-day delay ($\rho = 0.048$; $p < 0.001$). Two additional links indicated interactions with background checks. Link j represented a positive association, extending towards background checks with

Table 2. A list of the most followed Twitter accounts of anti- and pro-regulation organizations, along with their respective counts of followers and Twitter posts containing the keyword "Gun."

Category	Handle Name	Organization Name	Number of Followers	Number of Posts
Anti-regulation	nra	National Rifle Association	917.2K	16,527
	gunowners	Gun Owners of America	333.5K	8,463
	gunpolicy	Firearms Policy Coalition	215.5K	12,519
	usacarry	USA Carry	86.6K	34,849
	natlgunrights	National Association for Gun Rights	64.8K	6,356
	uscca	US Concealed Carry Association	64.8K	49,746
	blkgunsmattr	Black Guns Matter	43.5K	4,279
	bearingarmscom	BearingArms.com	25.3K	22,238
	naaganational	National African American Gun Association	14.8K	405
Pro-regulation	amarch4ourlives	A March for our Lives	440.4K	25,866
	momsdemand	Moms Demand Action	343.6K	37,289
	everytown	Everytown USA	267.6K	21,739
	giffordscourage	Giffords	104.7K	17,326
	bradybuzz	Brady: United Against Gun Violence	76.8K	15,316
	newtownaction	Newtown Action Alliance	46.4K	21,562
	csgv	Coalition to Stop Gun Violence	36.8K	58,865
	protesteasyguns	Protest Easy Guns	8,797	24,462
	efsgv	Educational Fund to Stop Gun Violence	3,830	2,511
	gunsdownamerica	Guns Down America	15K	2,599
	wagv	Women Against Gun Violence	22.5K	10,951

a delay of one day ($\rho = 0.048$; $p = 0.092$), whereas link m represented a negative association, extending away from background checks with a two-day delay ($\rho = 0.059$; $p = 0.001$).

The remaining five associations connected background checks with different types of media coverage. Links k and l represented associations between background checks and media coverage of firearm laws, oriented in opposite directions ($p < 0.001$). Both associations were positive ($\rho = 0.084$ and 0.099, respectively) and consisted of a single-day delay. Links f, h, and i connected background checks with media coverage of violent crime with delays of one, seven, and six days, respectively. One link, h, consisted of a negative association ($\rho = -0.075$), whereas the other two, f and i, indicated a positive association ($\rho = 0.105$ and 0.054, respectively).

The node corresponding to background checks was most connected, with four links directed towards it, three links extending away from it, and one unorientable link. Both media coverage of firearm laws and regulations and media coverage of violent crimes had seven links. Media coverage of firearm laws and regulations had three outgoing, two incoming links, and two unorientable links, whereas media coverage of violent crimes had four links directed towards it and three links extending from it. Media coverage of mass shootings was associated with four links: two facing outwards, one facing inwards, and one unorientable. Finally, activity of interest groups were the least connected nodes in the recovered network. Tweets by anti-regulation organizations influenced two other nodes and were influenced by one, whereas tweets by pro-regulation organizations were influenced by a sole node only.

Our analysis revealed expected and unexpected results. The presence of contemporaneous links was not surprising. The time series of media coverage of mass shootings and media coverage of violent crimes encompass different aspects of violence: the former majorly refers to mass murder carried out with firearms. In contrast, the latter could refer to any crimes carried out with any means. However, the time series likely share some

Table 3. Results for ADF and KPSS stationarity tests performed on seasonally adjusted and detrended time series.

Variable	ADF p-value	KPSS p-value
Background checks	3.703×10^{-3}	> 0.1
Media coverage of firearm laws and regulations	2.092×10^{-5}	> 0.1
Media coverage of mass shootings	2.439×10^{-22}	> 0.1
Media coverage of violent crime	6.410×10^{-9}	> 0.1
Tweets by pro-regulation organization	65.700×10^{-30}	> 0.1
Tweets by anti-regulation organization	1.041×10^{-1}	> 0.1

information whereby mass shootings can be considered a type of violent crime. As such, it is not surprising that when news about violent crime break, news about mass shootings break within the same day (link d). The direction of this association from the former to the latter could reflect preliminary reporting of a mass shooting event as a violent crime before details are fully unraveled and the event is deemed a mass shooting. Likewise, the contemporaneous link from media coverage of firearm laws and regulations to media coverage of violent crime (link b) was intuitive. It is reasonable that articles about firearm policies that allowed a perpetrator to obtain a weapon or could have prevented them from gaining access to weapons will co-occur with news about violent crimes with firearms. In this case, the direction of the association depicts the process whereby media initially report about legislative directions and later provide context of past violent crimes that could have been averted should a law had existed. This mechanism is independent of the nature of legislation as restrictive laws could prevent criminals from bearing firearms and permissive laws

Table 4. Summary of the links identified by the PCMCI+ algorithm.

Link	Source variable	Sink variable	Delay (days)	p-value	Partial correlation coefficient ρ
a	Media coverage of mass shootings	Media coverage of firearm laws and regulation	1	<0.001	0.094
b	Media coverage of firearm laws and regulation	Media coverage of violent crime	0	<0.001	0.100
c	Media coverage of mass shootings	Media coverage of violent crime	1	0.001	0.083
d	Media coverage of violent crime	Media coverage of mass shootings	0	0.001	0.071
e	Media coverage of firearm laws and regulation	Tweets by pro-regulation organizations	2	<0.001	−0.069
f	Background checks	Media coverage of violent crime	1	<0.001	0.105
g	Tweets by anti-regulation organizations	Media coverage of violent crime	2	0.009	0.048
h	Media coverage of violent crime	Background checks	7	<0.001	−0.075
i	Media coverage of violent crime	Background checks	6	0.035	0.054
j	Tweets by anti-regulation organizations	Background checks	1	0.092	0.048
k	Media coverage of firearm laws and regulation	Background checks	1	<0.001	0.084
l	Background checks	Media coverage of firearm laws and regulation	1	<0.001	0.099
m	Background checks	Tweets by anti-regulation organizations	2	0.001	0.059

could allow victims to protect themselves. Relatedly, the co-occurrence of media coverage of mass shootings and media coverage of firearm laws and regulations was not surprising. Although mass shootings account for a small fraction of firearm deaths [96], they are very impactful in terms of public response: following these events, public discourse on firearms, firearm prevalence, and firearm regulation intensifies and prepares the ground for legislative action [97]. Therefore, news about both variables could be released concurrently. Since the two topics are deeply intertwined, the presence of a link from media coverage of mass shootings to media coverage of firearm laws and regulations with a delay of one day (link a) is also highly conceivable. Finally, the unorientable contemporaneous link between background checks and media coverage of firearm laws and regulations could possibly demonstrate the causal link identified in Porfiri et al. [50], where people purchase firearms after they hear about upcoming regulations. This result suggests this behavior occurs within a single day.

In further agreement with Porfiri et al. [50], we found that background checks are influenced by media coverage of firearm laws and regulations (links k). Interestingly, we also found that background checks are influenced by media coverage of violent crimes (links h and i), indicating that many Americans purchase firearms for self-protection, although, they would act on this urge within the span of a week. These new two links, which were absent in previous studies with monthly time series [50, 55, 56], confirm our hypothesis that firearm acquisition in the US is driven by slow and fast processes, and that analyses with finer temporal resolution could reveal faster dynamics.

Finally, our analysis revealed four links associated with the activity of interest groups on Twitter. Media coverage of firearm laws and regulations preceded Tweets by pro-regulation organizations by two days (link e), however, this association was found to be negative. Therefore, this link could reflect the efforts of those organizations to raise awareness towards legislation when it is not reported by the media. At the same time, our results did not support the notion that pro-regulation organizations capitalize on the occurrence of mass shooting events or violent crimes to promote their agenda [61]. With respect to anti-regulation organizations, we found that their activity on social media influences media coverage of

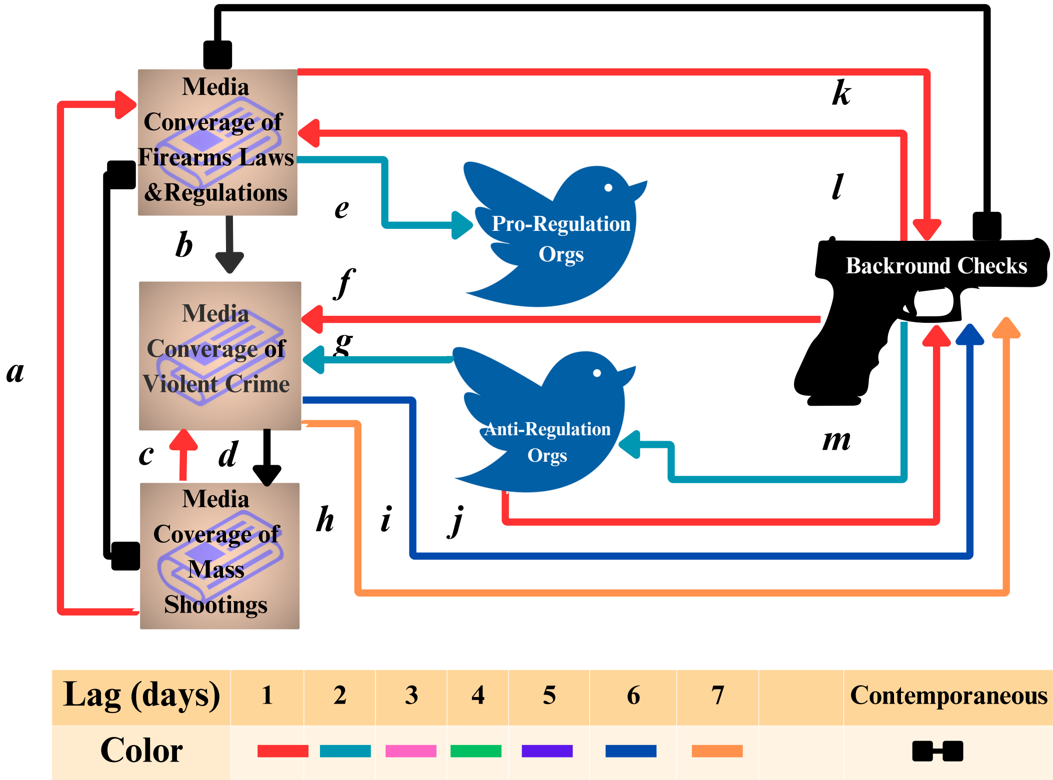

Fig. 2. Causal diagram generated through PCMCI+ for the six variables under consideration. The colors of links reflect the time delay between the two variables they connect. Black links represent contemporaneous associations (zero-day delay), with square endings indicating that the link is non-orientable. Red, teal, pink, green, purple, blue, and orange arrows reflect associations with delays of one, two, three, four, five, six, and seven days, respectively. Links for delays of three, four, and five days were not recovered in the analysis.

violent crime (link g) with a delay of two days. Although anti-regulation organizations publish less content following mass shootings and high-profile violent crimes [59, 61], their activity on social media might influence media narratives over time. In fact, the two-day delay between anti-regulation organizations' tweets and increased media coverage of violent crime could be commensurate with the time needed for those organizations to gain attention from mass media on such platforms. By emphasizing legislative issues, anti-regulation organizations may indirectly prompt media outlets to frame violent crime stories within policy debates on firearm regulations. This suggests their strategic focus contributes to shifts in media coverage after a short delay. The activity of anti-regulation organizations on Twitter was also bidirectionally associated with background checks. Link j (from the former to the latter) is somewhat intuitive as it suggests that Twitter posts by anti-regulation organizations, whose followership encompasses potential firearm buyers, elicit greater firearm acquisition. In contrast, link m (from the latter to the former) was unexpected. In addition to link m, our analysis points to two less expected links: from background checks to media coverage of violent crime (link f) and from background checks to media coverage of firearm laws and regulations (link l). We acknowledge that these links are not intuitively explained and may require additional analyses involving additional nodes in the graph.

Conclusion

Firearms are central to American culture and identity, yet firearm injuries are a leading cause of death in the US. Understanding the drivers of firearm acquisition is an essential first step to comprehending and curbing firearm harms, without infringing on citizens' right to bear arms. In this study, we performed causal analysis using the PCMCI+ framework [68] to elucidate the relationships between five potential drivers of firearm acquisition and firearm acquisition itself. This analysis extends on previous work from our group [50], showing that firearm acquisition in the US is primarily driven by media coverage of firearm laws and regulations, and not by media coverage of shootings, nor by the incidence of mass shooting events. Compared to Porfiri et al. [50], the innovations in the present study are three times.

First, we investigate interactions that take place within days rather than months. Such an analysis with finer temporal resolution could reveal faster dynamics and unveil certain links that were previously absent [50]. Second, we consider media coverage of mass shootings (rather than the incidence of mass shootings themselves) and media coverage of violent crimes. Research has shown that the amount of media coverage of criminal events is disproportionate to actual crime rates [95, 98] and that stories of criminal events are often sensationalized to capitalize on emotional narratives and draw more attention from the public [99, 100]. Time series of media coverage of mass shootings and violent crimes may better correlate with people's concern for their personal safety and tendency to purchase firearms rather than time series that directly measure the occurrence of those events.

Third, we introduce two new nodes into the complex system that reflect the activities of anti- and pro-regulation organizations. The activity of both pro- and anti-regulation organizations does not peak following mass shooting events, such that the time series possibly reflect ongoing public discourse about firearm regulation.

This study investigates the dynamics of mass media, the activity of interest groups on social media, and their influence on gun purchases. Nonetheless, our findings come with several limitations.

First, the time series generated for this study may not fully reflect the public's sentiment, discourse, or behavior. While background checks are commonly used as a proxy of firearm acquisition rates [32, 50, 56, 86], they fail to capture legal and illegal private party sales [32, 85]. Alternative proxies of firearm ownership exist [7, 16], however, data on those variables are not available with daily resolution.

Similarly, the time series of media coverage of firearm-related topics count new articles in ten print media outlets. Although the selected outlets represent both liberal and conservative readerships across the US regions, the time series does not account for news reports from other means where people learn about current events including television, radio, and the internet. Thus, inferring the public's perception of crimes or knowledge of looming regulations from the time series may be inaccurate. Finally, the time series of tweets published by interest groups do not fully represent their activities and engagement with the public, as outreach could include interactive communication through comments and microvlogging, and in-person meetings [75, 101]. This limitation comes as a cost of performing granular analysis with difficult-to-access daily data. Nonetheless, our results offer preliminary albeit circumspect insights into the drivers of firearm acquisition in the US.

Related to this limitation, one could argue that the use of national-level time series leads to loss of state-level nuisances. Research has firmly indicated that firearm ownership varies among states, strongly affected by urbanization, demographics, socioeconomics, culture, and politics [8, 12, 19, 20, 56, 102, 103]. Crimes rates and their nature also widely vary among states and regions [104, 105], and interest groups invest different levels of lobbying effort in each state [106]. Ideally, the analysis presented herein would be conducted on a state level, however, daily data on background checks are not available nor is it feasible to collect geolocated data on media coverage of firearm-related topics and the activity of interest groups. Should such data become available, state-level analysis would be strongly warranted.

Second, the time series of media coverage originate in print media, whereas the time series of anti-and pro-regulation organizations come from social media. Print media is a slower means for publishing current events than digital media. That is, newspapers are distributed a day after events took place, whereas social media reflect events in real-time [80]. This difference may have introduced a false delay in certain interactions. While news can be consumed through multiple fast-paced sources, tools that systematically record the content of news items in those media do not exist, and scraping such large-scale information from the internet is not feasible [107]. An alternative approach to gauge public discourse might entail "infodemiology", an emerging branch of science that queries determinants of information in digital media through social networks as well as search engines and other interfaces people engage with electronically [90, 108].

A third limitation in our study is the use of counts of Twitter posts without regard to their content. Future analysis could consider the sentiment and stance to quantitatively measure the kind of content anti- and pro-regulation organizations publish [89, 109]. However, working with Twitter posts may provide limited information about the message organizations try to convey. In their study, Merry measured the "narrativity" of Twitter posts by the National Rifle Association and the Brady Campaign [60]. For both organizations, they found that narrativity was lower than in other media and attributed this result to the platform's limit of 140 characters. Further, although interest groups likely post content on all of their social media channels simultaneously, it is possible that including other outlets would have yielded different results as more narrated content is released to the public.

Finally, any evidence for contemporaneous links involving background checks or non-contemporaneous links that extend to/from background checks to other variables warrants cautious interpretation. Requests for background checks are submitted to NICS in a non-uniform manner and may not reflect the time a federally licensed firearm dealer submits a request accurately [85]. When considering monthly time series, these uncertainties are mitigated to some extent. However, using daily data, we must consider that the delays associated with links are spurious.

Overall, there are several take-home messages from this work. Concerning the temporal resolution of data, the results show a marked difference when comparing analyses with daily and monthly time series. Although daily studies offer a more immediate view, monthly analyses provide an encompassing perspective, which can be instrumental in discerning longer-term trends and subtler interconnections. Regarding the drivers of firearm acquisition, while media coverage of violent crimes and firearm regulations may influence citizens' choice to purchase a weapon, also the activity of relevant interest groups has direct implications on making this decision. Since candidate firearm owners are likely to subscribe to anti-regulation channels, these organizations directly influence firearm acquisition, not pro-regulation organizations. With the understanding that media coverage of violent crime may drive firearm acquisition, as well as the activity of anti-regulation organizations, legislators and policymakers are advised to target those aspects of the network to discourage firearm acquisition without limiting Americans' right to bear arms.

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Supplementary Material

Supplementary material is available at PNAS Nexus online.

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Author contributions statement

K.D., K.S., M.P., and I.B. designed the study. K.D., K.S., R.S., R.B.V., M.P., and I.B. performed research. K.D. and K.S. collected the data, K.D., K.S., R.S., and R.B.V. performed analysis. M.P. and I.B. supervised research. R.B.V. managed the project and drafted the manuscript. K.D., K.S., R.S., R.B.V., M.P., and I.B edited the manuscript and provided feedback on all drafts.

Ethics statement

The analysis involved publicly available and non-identifiable data. No direct interaction or intervention with human subjects took place during the study, and all data were presented in aggregated amounts. As such, ethics approval was not sought from the authors' respective institutional review boards.

Conflict of interests

None declared.

Abbreviations

ADF: Augmented Dickey-Fuller
KPSS: Kwiatkowski–Phillips–Schmidt–Shin
PCMCI: Peter-Clark Momentary Conditional Independence
US: United States

Data availability

The data sets and codes used in the study are available on GitHub (https://github.com/Belykh-Lab/twitter-effect-supplemental).

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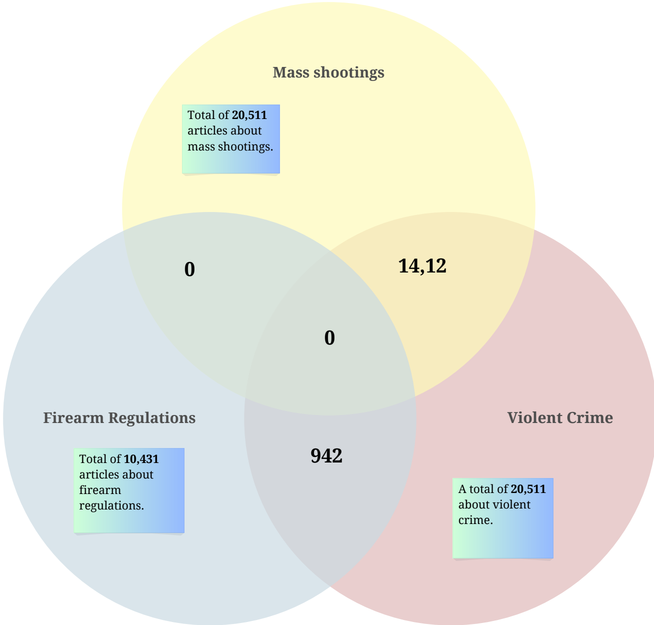


Supplementary Figure 1. Venn diagram showing the number of newspaper articles shared between the three time series of media coverage. More than 90% of the articles in each pair of time series are not shared.

Supplementary Information for “How advocacy groups on Twitter and media coverage can drive U.S. firearm acquisition: a causal study.”

Media Coverage of Firearm-Related Topics

We collected three time series from ProQuest, each containing the number of newspaper articles published on a firearm-related topic. The search queries used to generate the time series are listed in Supplementary Table 1. While the search terms for each topic were distinctly different, it is possible that the time series shared a substantial number of articles among them. For instance, the time series of media coverage of mass shootings and violent crimes could have shared a large number of articles, as mass shootings can be considered a type of violent crime. If this were the case, the time series generated would not be independent, and inference of causal relationships between them would be spurious.

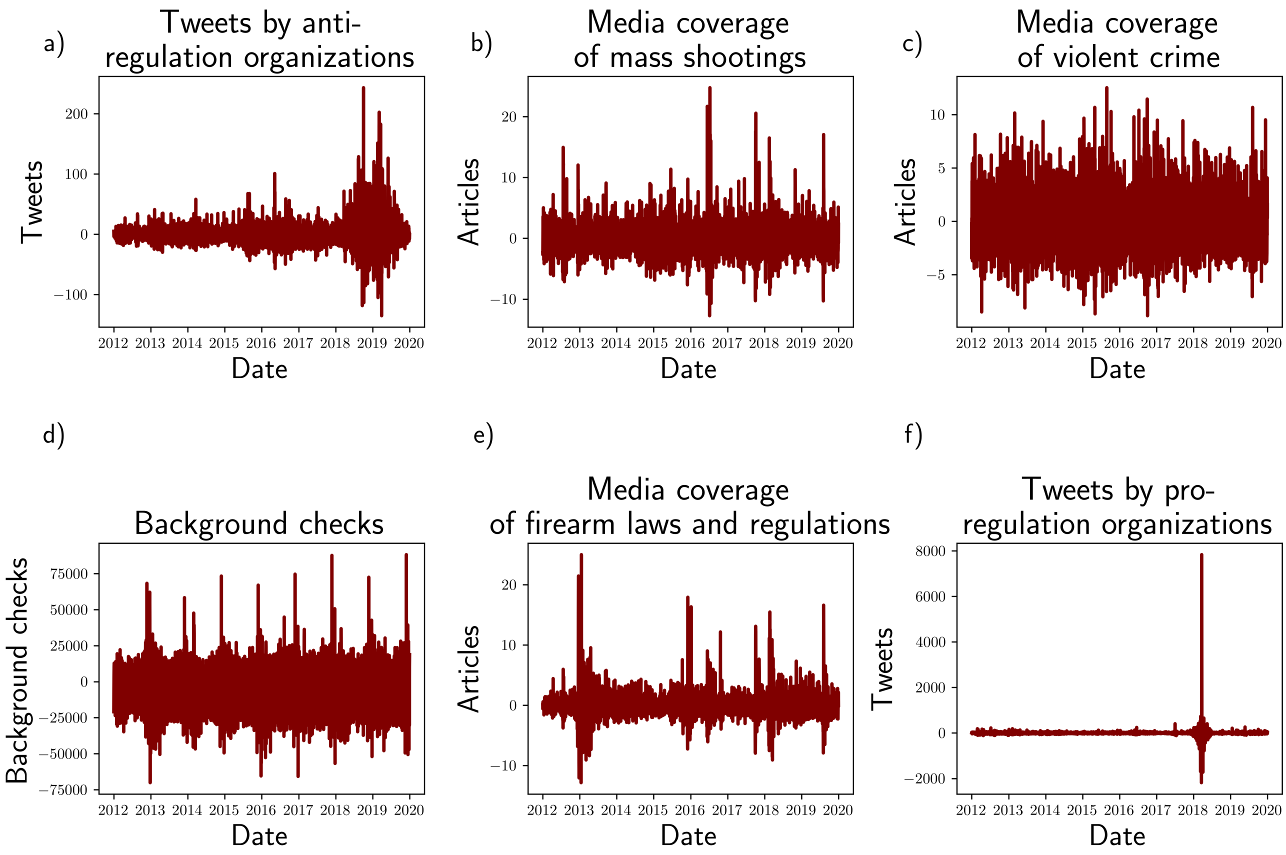
In Supplementary Figure 1, we present a Venn diagram showing the number of newspaper articles shared between the time series of media coverage. While no articles are shared between media coverage of mass shootings and firearm laws and regulations, 942 articles are shared between media coverage of violent crimes and firearm laws and regulations, and 1412 between media coverage of violent crimes and mass shootings. In both cases, the number of shared articles represents less than 10% of the total counts in either time series. Therefore, the time series capture largely distinct processes.

Time Series Processing

The raw time series we gathered could contain seasonality and/or trends that could give rise to incorrect inference of interactions in an information-theoretic framework. Therefore, we seasonally adjusted and detrended the time series using the “forecast” package in R (version 8.18). Specifically, we applied the `msts` function for periods of 1, 2, 3, 5, 7, 30, 31, 365.25/12, and 365.25 days, followed by the `mstl` function to decompose the time series into seasonal, trend, cycle, and irregular components. We then applied the augmented Dickey–Fuller test to ensure the stationarity of the seasonally-adjusted and detrended time series. Supplementary Figure 2 displays the processed time series for each of the six variables.

Time Series	**ProQuest Search Query**
Media coverage of firearm laws and regulations	(firearms laws) AND (publication.exact(”New York Times” OR ”Los Angeles Times” OR ”Chicago Tribune” OR ”Orlando Sentinel” OR ”St. Louis Post - Dispatch” OR ”Wall Street Journal” OR ”Arizona Republic” OR ”Denver Post” OR ”Times - Picayune” OR ”Houston Chronicle”) AND stype.exact(”Newspapers”) AND subt.exact(”firearm laws & regulations”) AND pd(20120101-20200101))
Media coverage of mass shootings	(Shootings) AND (publication.exact(”New York Times” OR ”Los Angeles Times” OR ”Chicago Tribune” OR ”Orlando Sentinel” OR ”St. Louis Post - Dispatch” OR ”Wall Street Journal” OR ”Arizona Republic” OR ”Denver Post” OR ”Times - Picayune” OR ”Houston Chronicle”) AND stype.exact(”Newspapers”) AND subt.exact((”shootings” OR ”mass murders”) NOT ”firearm laws & regulations”) AND pd(20120101-20200101))
Media coverage of violent crimes	(violent crime) AND (publication.exact(”New York Times” OR ”Los Angeles Times” OR ”Chicago Tribune” OR ”Orlando Sentinel” OR ”St. Louis Post - Dispatch” OR ”Wall Street Journal” OR ”Arizona Republic” OR ”Denver Post” OR ”Times - Picayune” OR ”Houston Chronicle”) AND stype.exact(”Newspapers”) AND pd(20120101-20200101))

Supplementary Table 1. ProQuest search queries used to collect the daily number of newspaper articles on firearm-related topics.



Supplementary Figure 2. Seasonally adjusted and detrended time series of the variables considered in the study: (a) media coverage of firearm laws and regulation, (b) media coverage of mass shootings, (c) media coverage of violent crime, (d) tweets by pro-regulation organizations, (e) tweets by anti-regulation organizations, and (f) background checks.