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Media coverage and firearm acquisition in the aftermath of a mass shooting

Maurizio Porfiri[1,2]*, Raghu Ram Sattanapalle[1], Shinnosuke Nakayama[1], James Macinko[3] and Rifat Sipahi[4]

With an alarming frequency, the United States is experiencing mass shooting events, which often result in heated public debates on firearm control. Whether such events play any role in recent dramatic increases in firearm prevalence remains an open question. This study adopts an information-theoretic framework to analyse the complex interplay between the occurrence of a mass shooting, media coverage on firearm control policies and firearm acquisition at both national and state levels. Through the analysis of time series from 1999 to 2017, we identify a correlation between the occurrence of a mass shooting and the rate of growth in firearm acquisition. More importantly, a transfer entropy analysis pinpoints media coverage on firearm control policies as a potential causal link in a Wiener–Granger sense that establishes this correlation. Our results demonstrate that media coverage may increase public worry about more stringent firearm control and partially drive increases in firearm prevalence.

As summarized by the US Congressional Research Service (CRS), from 1999 to 2013, the United States experienced on average 31 mass murders per year, in which 4 or more people were killed in a single incident[1]. Two-thirds of these incidents were considered by the CRS to be 'mass shootings', where the perpetrator committed the murder by exclusively using firearms[1]. From the 317 mass shootings documented in the 15-year CRS report, 1,554 people lost their lives and 441 were non-fatally wounded[1]. Using the same definition and extending these observations to 2017, the count exceeds 2,000 individuals killed and over 1,000 wounded victims, as documented on the Gun Violence Archive website[2].

In the wake of most of these shocking events, we consistently witness dichotomous opinions expressed through extensive media reporting and presentation of divisive debates. Some of these opinions propose that restricted firearm ownership would help to stop or reduce the epidemics of mass shootings. Others advocate the opposite: empowering people with firearms is the solution for reducing mass shooting casualties through deterrence and self-protection. It is tenable that media coverage on mass shootings may help to shape public opinion, thereby influencing firearm acquisition, but empirical research to evaluate the interplay between media coverage, mass shootings and firearm acquisition remains elusive.

The Second Amendment to the US Constitution protects the right of citizens to keep and bear arms. With a little over 4% of the world's population, the United States has the largest number of firearms among all upper-income countries[3–6]. The Federal Bureau of Investigation (FBI) reports over 275 million background checks to purchase firearms from licensed dealers from 1999 to 2017 and that firearm prevalence is accelerating[7]. Combining records of firearm manufacturing, export and import[8] with data from CRS[9], the total number of firearms in the United States reached 385 million in 2016, a figure that is 20% higher than the US population.

Federal statutes regulate all aspects of firearms, from their manufacturing, licensing and record keeping to their destruction. The major federal gun law is the 1993 Brady Handgun Violence Prevention Act, which mandates federal background checks on firearm purchases. While recent Supreme Court rulings have delimited the boundaries of firearm control policies[10], there are still opportunities for policymakers to modify the current legal landscape and push forward focused laws and regulations. In fact, because each US state may pass its own firearm-related laws, there are actually 50 highly divergent firearm regulatory environments in the United States. Specific firearm-related laws vary substantially from state to state, such that some states have much stricter regulations on the purchase, permitting, carrying and storage of firearms, whereas other states create fewer barriers to firearm acquisition and may even provide firearm owners greater legal protections, including 'stand your ground' and other laws[11].

The incipit of a recent survey by Pew Research Center (Washington DC, USA) reveals the complex relationship between firearms and the US population: "As a nation, the U.S. has a deep and enduring connection to guns. Integrated into the fabric of American society since the country's earliest days, guns remain a point of pride for many Americans"[12]. Whether it is for protection, hunting or sport shooting, three-quarters of gun owners—and one-third of those who are not gun owners—indicate that possessing a gun is essential to their sense of freedom[12]. Given this history and background, and the already high level of firearm possession in the United States, recent increases in firearm prevalence merit investigation.

As proposed in several reports, such as refs. [13–16], it is possible that in the aftermath of a mass shooting, individuals might fear that stricter control policies could be enacted, thereby challenging their ability to acquire a firearm in the future. As a result, they might opt to purchase a firearm immediately. Such a surge of firearm acquisition is not always triggered by mass shootings. For example, it has been empirically demonstrated that firearm acquisition increased when President Barack Obama took office in 2008 (ref. [17]). The main objective of this study is to empirically examine whether media coverage may provide a link between fear of stricter firearm controls

[1]Department of Mechanical and Aerospace Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA. [2]Department of Biomedical Engineering, Tandon School of Engineering, New York University, Brooklyn, NY, USA. [3]Department of Community Health Sciences and Department of Health Policy and Management, Fielding School of Public Health, University of California, Los Angeles, CA, USA. [4]Department of Mechanical and Industrial Engineering, Northeastern University, Boston, MA, USA. *e-mail: mporfiri@nyu.edu

and subsequent increases in firearm acquisition, even in the absence of new firearm-related regulations.

By focusing on six mass shootings between 2000 and 2010, recent work[18] offers empirical evidence supporting an association between mass shootings and increased national firearm acquisition, inferred from the nationwide number of background checks. Evidence in favour of an association between mass shootings and firearm acquisition is also presented by Studdert et al.[19], who report a large increase in the number of handgun sales in California following the Sandy Hook Elementary School shooting in December 2012 and the San Bernardino shooting in December 2015. Here, we build on these studies to elucidate the potential role played by media coverage on the association between mass shootings and firearm acquisition.

Towards this aim, we study multivariate interactions within the fundamental triad constituted by mass shootings, media output on firearm control topics and background checks used as a proxy for firearm purchases. Rather than focusing on a few representative mass shootings[18,19], we examine all 69 of the mass shootings from 1999 to 2017 reported on the *Mother Jones* website[20], which encompass incidents in a public place, excluding crimes related to gang activity or armed robbery. Beyond simple correlations between time series, we adopt an information-theoretic approach that is designed to test for influences between each possible pair of the triad. The framework is built on the information-theoretic construct of transfer entropy[21], which allows for the inference of directional interactions in networks of coupled dynamical systems[22]. Transfer entropy measures the extent to which the prediction of the future of a system from its present is improved due to additional knowledge about the present state of another system[21] and can be considered a form of causal inference in a Wiener–Granger sense[22].

Over the past two decades, we have seen a surge in applications of transfer entropy across the most disparate fields of science and engineering, in which the identification of influence between time series is needed. For example, neuroscientists have explored the feasibility of a transfer entropy-based approach to understand functional circuits in the brain[23,24], and climatologists have attempted to apply transfer entropy for reconstructing climate networks around the globe[25,26]. In the domain of public health, our group has explored the use of transfer entropy to identify leader–follower relationships among US states with respect to diffusion of motor vehicle safety regulations[27–29]. Understanding the interplay between mass shootings, media output and background checks poses important technical challenges with respect to these problems, due to the sparseness of the time series, the potential risk of indirect coupling between them and the seasonality of background checks.

We collected monthly background check data from January 1999 to December 2017, for a total of 228 recordings. At the national level, the data follow a very strong seasonal pattern, with peaks in December and lows in June or July (Fig. 1a). In addition to seasonal effects, the data present peaks following certain events; for example, the highest number of background checks at the national level ($n=2{,}171{,}293$) was recorded in December 2012, which follows the Sandy Hook Elementary School shooting. On average, 789,189 background checks are conducted every month in the United States. To control for the presence of seasonal effects and global trends, we performed a seasonality adjustment, followed by a detrending (Fig. 1b). The augmented Dickey–Fuller test indicates stationarity for the seasonally adjusted and detrended background check time series (Dickey–Fuller $t=-4.306$, $P=0.004$).

Monthly data on the occurrence of mass shootings from January 1999 to December 2017 were compiled from the *Mother Jones* mass shooting database, which collates data from news and official reports. The data consist of 69 mass shooting events from January 1999 to December 2017 (Fig. 1c). These mass shootings are not distributed equally over time. On average, since 1999, there has

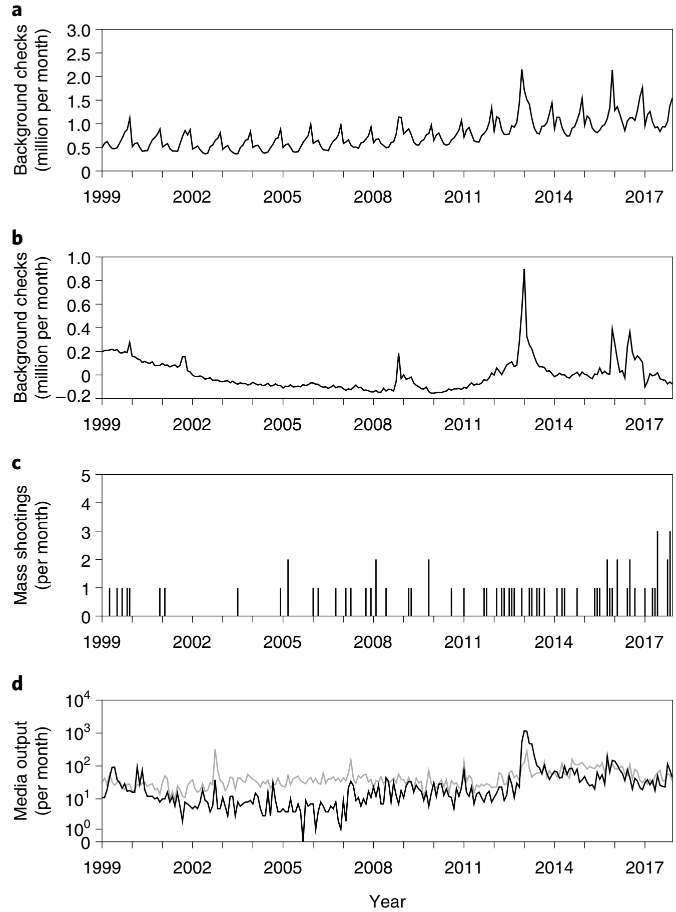

Fig. 1 | Time series for the study of the relationships between firearm acquisition, mass shootings and media coverage on firearm control policies from January 1999 to December 2017. a, Time series of the number of firearm background checks. **b**, Seasonally adjusted and detrended time series of the number of firearm background checks. **c**, Number of mass shootings. **d**, Media output (number of documents) mentioning firearm laws or regulations (black) and shootings excluding firearm laws or regulations (grey) on the scale of inverse hyperbolic sine transformation.

been a mass shooting every 3.3 months; however, the frequency of mass shootings has been increasing. For the first decade, from 1999 to 2008, there has been one mass shooting every 5.7 months, while from 2009 to 2017, there has been one mass shooting every 2.3 months (using the pre-2013 definition by *Mother Jones*, this reduces to one mass shooting every 3.0 months). The average age of the shooter was 35 years, and more than half of the shootings were carried out by white males (36 out of 69). Of the 69 mass shootings, 47 were carried out with legally obtained firearms, 10 with illegal firearms, and firearms used in the remaining 12 were obtained through unknown sources. The augmented Dickey–Fuller test for the occurrence of mass shooting time series indicates stationarity (Dickey–Fuller $t=-15.180$, $P<0.001$).

We collected all documents with the heading "Firearm Laws and Regulations" (all document types, including news reports, commentaries, editorials, articles and features), published in *The New York Times* and *The Washington Post*, by month, from January 1999 to December 2017 (Fig. 1d). The search returned 9,756 results in total. The average monthly media output was 43 documents with the highest value of 1,175 recorded in January 2013, in the aftermath of the Sandy Hook Elementary School shooting, which led to

Table 1 | Influences between variables (mass shootings, media output and background checks) estimated through conditional transfer entropy

	Mass shootings	Media output	Background checks
Media output on firearm laws and regulations			
Mass shootings	—	0.0086 (0.0328), $P=0.626$	0.0134 (0.0324), $P=0.403$
Media output	0.0114 (0.0322), $P=0.492$	—	**0.0389** (0.0317), $P=0.020$
Background checks	0.0184 (0.0325), $P=0.241$	0.0029 (0.0323), $P=0.935$	—
Media output on shootings (excluding firearm laws and regulations)			
Mass shootings	—	**0.0345** (0.0322), $P=0.039$	0.0111 (0.0314), $P=0.497$
Media output	0.0082 (0.0324), $P=0.657$	—	0.0018 (0.0317), $P=0.967$
Background checks	0.0146 (0.0317), $P=0.361$	0.0267 (0.0314), $P=0.089$	—

Rows are sources and columns are targets. The numbers in parentheses denote the 95% quantile obtained from a permutation test, in which each observed value was compared with the random values estimated from 50,000 surrogate time series. A bold value indicates a significant positive conditional transfer entropy at $\alpha=0.05$.

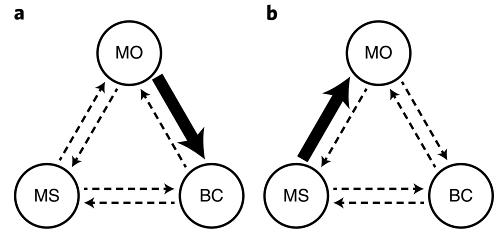

Fig. 2 | Estimated conditional transfer entropy between each pair of mass shootings, media output and firearm background checks. a, Media output (MO) on firearm laws and regulations. **b**, Media output on mass shootings (MS), excluding firearm laws and regulations. The solid arrows indicate significant transfer entropy, and the dashed arrows indicate non-significant transfer entropy. The same data are in Table 1. BC, background checks.

widespread debate about firearm legislation changes and the formation of an inter-agency gun violence task force headed by the then Vice President, Joe Biden. The augmented Dickey–Fuller test for the media output time series indicates stationarity (Dickey–Fuller $t=-7.011$, $P<0.001$).

Kendall's correlation coefficient between background checks and media output suggests that there is a positive correlation between them ($\tau=0.287$, $z=6.382$, $P<0.001$). Similarly, we identify a positive correlation between mass shootings and background checks ($\tau=0.123$, $z=2.299$, $P=0.022$) and between mass shootings and media output ($\tau=0.227$, $z=4.208$, $P<0.001$). Therefore, the number of background checks increases with the number of mass shootings, and both of these variables increase with relevant media output.

To delve into these correlations and tease out potential causal links between the three variables, we performed a conditional transfer entropy analysis. Table 1 summarizes the conditional transfer entropy results for all six possible combinations of the three variables. We identify significant transfer entropy from media output to background checks (0.0389, against the 95% quantile of the null distribution 0.0317 from 50,000 permutations, $P=0.020$), after controlling for mass shootings. No further significant transfer entropy values are noted in other pairs of variables (from mass shootings to media output, 0.0086, against the 95% quantile 0.0328, $P=0.626$; from mass shootings to background checks, 0.0134, against the 95% quantile 0.0324, $P=0.403$; from media output to mass shootings, 0.0114, against the 95% quantile 0.0322, $P=0.492$; from background checks to mass shootings, 0.0184, against the 95% quantile 0.0325, $P=0.241$; and from background checks to media output, 0.0029, against the 95% quantile 0.0323, $P=0.935$), following conditioning on the third one (Fig. 2a). Should one opt to pursue a pairwise information-theoretic analysis to measure the extent to which the future of one variable is explained by the present of the other variable, they would obtain equivalent predictions (Supplementary Table 2).

Granularly exploring each US state, we found a significant influence of the restrictiveness of firearm-related laws on transfer entropy from media output to background checks, after controlling for mass shootings (Fig. 3a–c). The magnitude of conditional transfer entropy is explained by the variation in the restrictiveness of firearm-related laws among states, such that people in states with more relaxed policies show larger transfer entropy from media output to background checks (gamma generalized linear model (GLM), $\chi_1^2=37.483$, $P<0.001$), after controlling for mass shootings. Although we excluded Connecticut and Hawaii from the analysis due to missing or anomalous data, including them does not substantially change this result ($\chi_1^2=24.228$, $P<0.001$). States with significant conditional transfer entropy have less restrictive firearm-related laws (Alabama, Arizona, Arkansas, Florida, Idaho, Kansas, Nevada, North Dakota, Ohio, Oregon and Virginia) than those states with non-significant conditional transfer entropy (Fig. 3d; Welch's t-test, $t=2.773$, d.f. $=44.7$, $P=0.008$). Although Iowa has a marginally significant conditional transfer entropy ($P=0.051$), removing Iowa from the analysis does not substantially change the result ($t=2.736$, d.f. $=43.3$, $P=0.009$). We further investigated firearm-related laws by categories, such as laws regarding dealer regulations, buyer regulations and child access restrictions, and found similar results (Supplementary Figs. 1–11).

Finally, to investigate the possibility that people obtain firearms for reasons other than fear of more stringent control policies after mass shootings, we collected all documents with the heading "Shootings", but excluding "Firearm Laws and Regulations". The search returned 10,832 documents, with an average monthly media output of 47.5 (Fig. 1d). Virtually all documents were related to firearm violence, evidenced by the shared headings (3,510 documents with "Murder and Murder Attempts", 2,424 documents with "Criminal Investigations", 1,233 documents with "Deadly Force", 1,028 documents with "Police" and 1,012 documents with "Mass Murders"). The highest value of 313 recorded in October 2002 coincides with the Washington DC sniper attacks, in which 2 shooters killed 10 people in Maryland, Virginia and the District of Columbia over 3 weeks. Following the previous analysis, we studied conditional transfer entropy for the triad consisting of mass shooting, media output on shooting excluding firearm laws and regulations, and background checks. The augmented Dickey–Fuller test for this media output time series indicates stationarity (Dickey–Fuller $t=-10.767$, $P<0.001$).

Correlation tests suggest a positive association between this media output and both mass shootings ($\tau=0.249$, $z=4.635$, $P<0.001$) and background checks ($\tau=0.094$, $z=2.100$, $P=0.036$). By contrast, we found significant transfer entropy from mass shootings to media output (0.0345, against the 95% quantile of the null

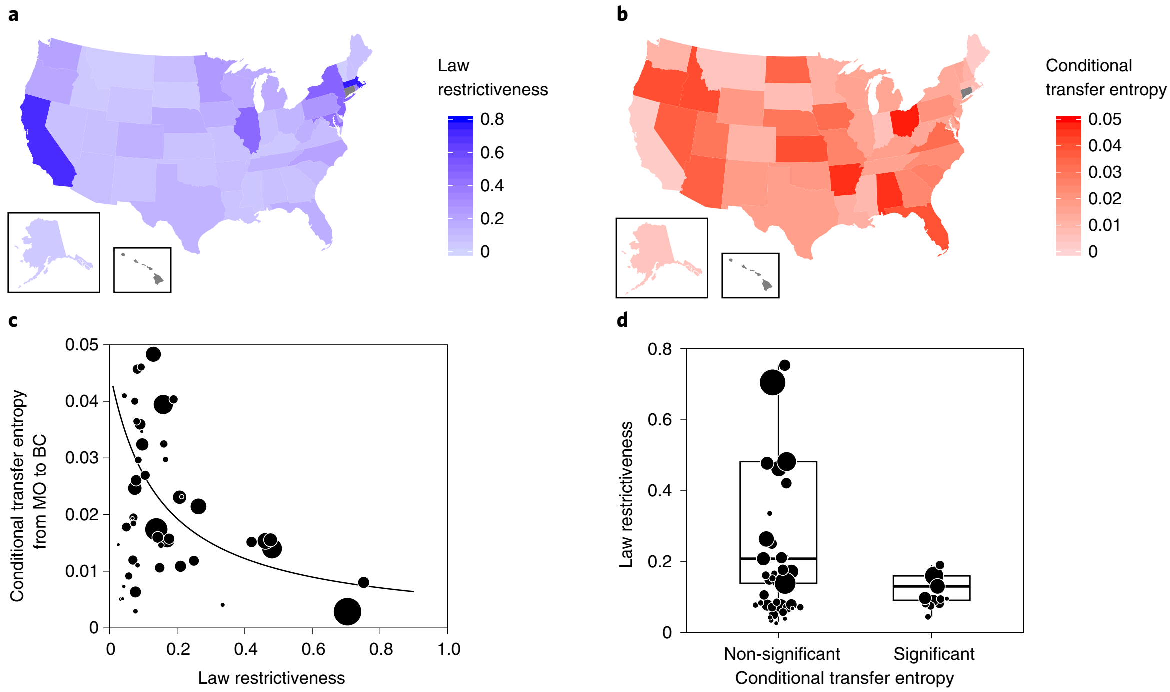

Fig. 3 | Restrictiveness of firearm-related laws and transfer entropy from media coverage on firearm control polices to background checks, after controlling for mass shootings. a, Firearm law restrictiveness based on the average proportion of effective firearm-related laws from 1999 to 2017. **b**, Transfer entropy from media output on firearm laws and regulations to background checks, after controlling for mass shootings. The grey colour indicates the states excluded from the analysis due to a lack of data (Hawaii and Connecticut). **c**, Relationship between firearm law restrictiveness and transfer entropy from media output on firearm laws and regulations to background checks, after controlling for mass shootings. The line indicates the model fit (gamma GLM, $\chi_1^2=37.483$, $P<0.001$). **d**, Contrast in the firearm restrictiveness score between states with non-significant magnitudes of transfer entropy and those with significant magnitudes of transfer entropy (Welch's t-test, $t=2.773$, d.f. $=44.7$, $P=0.008$). The centre line represents the median, the limits of the box are the upper and lower quartiles, and the whiskers indicate 1.5 times the interquartile range above the upper quartile and below the lower quartile. The symbol size corresponds to the state population.

distribution 0.0322 from 50,000 permutations, $P=0.039$), after controlling for background checks, but failed to detect transfer entropy from media output to background checks (0.0018, against the 95% quantile 0.0317, $P=0.967$; Table 1), after controlling for mass shootings (Fig. 2b). Results for all six possible combinations of the three variables are summarized in Table 1. Should one opt to pursue a pairwise information-theoretic analysis, no link between variables would be detected, not even that from mass shootings to media output (Supplementary Table 3).

As a third case of media output not directly related to firearms, we considered articles on unemployment, which should inform about social disorganization and violent crime[30]. When conducting the conditional transfer entropy analysis using media output on unemployment, we did not find significant transfer entropy from media output to background checks (0.0124, against 95% quantile of the null distribution 0.0314 from 50,000 permutations, $P=0.441$), after controlling for mass shootings, or any other combination within the triad (from mass shootings to media output, 0.0186, against the 95% quantile 0.0322, $P=0.238$; from media output to mass shootings, 0.0034, against the 95% quantile 0.0324, $P=0.901$; from mass shootings to background checks, 0.0156, against 95% quantile 0.0318, $P=0.322$; from background checks to mass shootings, 0.0162, against the 95% quantile 0.0319, $P=0.309$; and from background checks to media output, 0.0225, against the 95% quantile 0.0324, $P=0.156$; Supplementary Table 4).

The validity of the adopted information-theoretic approach was tested on synthetic data, generated through a mathematical model whose interactions are known a priori (see Supplementary Information). Using synthetic time series of 19 years, we found that the information-theoretic approach is successful in detecting a true link and simultaneously dismissing false links (area under the curve $=0.946$; Supplementary Figs. 15 and 16 and Supplementary Table 5).

In conclusion, in the wake of a mass shooting, the media extensively covers the topic of firearm laws and regulations, bringing forward divergent viewpoints and hypothetical scenarios that resonate with the public. Many firearm control advocates regard the aftermath of a mass shooting to be a fertile policy window: as people's attention is captured by these gruesome incidents, more restrictive policies might gain traction among policymakers, and legislatures may become more amenable to change. However, this increased attention may elicit a parallel reaction, in which people may fear that their access to firearms will be soon restrained and, thus, opt to purchase firearms before this happens. The present study offers empirical evidence in favour of such a snowball effect, in the form of a directed link from media coverage on firearm control policies to firearm acquisition nationwide and in states with less restrictive firearm laws.

In this work, we adopted a data-driven methodology that seeks to infer plausible causal relationships beyond the correlation analyses often performed in the literature. Our model-free, information-theoretic approach allows for multivariate analysis of the fundamental triad composed of mass shootings, media coverage on firearm control policies, and firearm acquisition as measured through background checks. From the time series of these variables, we quantify the influence of each variable on the others via the mathematical construct of transfer entropy. In a Wiener–Granger causality sense[22], influence is measured as an improved ability to predict the future of a variable from its present, due to additional knowledge about the present of another variable. From this perspective, the link between media coverage on firearm control policies and firearm acquisition corresponds to the improved ability to predict variations in the number of background checks in a given month from past background checks, due to additional knowledge about changes in media coverage on firearm control policies.

As discussed by Luca et al.[31], there have been, on average, more than 30,000 firearm-related fatalities in the United States per year over the 25-year period from 1989 to 2014, and mass shootings (using a similar definition to *Mother Jones*) amount to a very small fraction (0.13%) of these firearm-related deaths. However, previous efforts have identified a robust association between mass shootings and firearm acquisition, such that more firearms will be acquired in the aftermath of a mass shooting[18,19]. In agreement with these studies, we identify a correlation between the incidence of a mass shooting and increases in firearm prevalence, such that greater background checks will be registered in months when one or more mass shootings occur. However, accounting for the effect of media coverage on firearm control policies in our information-theoretic multivariate analysis, the association between mass shootings and background checks loses significance. We find that variations in the number of background checks are not explained by the occurrence of a mass shooting, nor are the occurrences of mass shootings explained by variations in the number of background checks. These results suggest that observations in previous reports on the link between specific mass shooting events and new firearm acquisition might be mediated by media coverage on firearm control policies.

The lack of a direct influence of mass shootings on background checks is in line with our predictions, in which the effect of a specific mass shooting on people's decision-making should be highly mediated by the level of coverage that the media devote to that specific incident. As a result, we initially anticipated that the time series of the incidence of mass shooting alone would not constitute a useful predictor of firearm acquisition. Some incidents, more than others, have catalysed vibrant, divisive discussions and extensive societal debates on the need of tighter firearm control policies[32,33], thereby explaining the lack of significant transfer entropy from mass shootings to media output on firearm laws and regulations. By contrast, media output on shootings that exclude discussion of firearm laws and regulations was predicted by the occurrence of mass shootings, as one might expect from the nature of the media of reporting such news. Our inference is in partial disagreement with empirical evidence by Wallace[18], in which the association between mass shootings and increased background checks was found to be robust with respect to selected proxies for the fear of increased firearm restrictions. However, numerous methodological differences exist between our study and this previous work. First, we looked at 69 mass shootings, whereas only 6 are considered by Wallace[18]; second, we considered a data set from 1999 to 2017, whereas Wallace[18] focuses on the 10-year period 2000–2010; third, our information-theoretic approach does not presume linear interactions among the variables, which is inherent in the statistical model used by Wallace[18]; and, last, we quantified fear of increased firearm restrictions from media coverage on firearm control policies, instead of relying on Google searches for the terms "gun law", "gun control", "gun restrictions" or the election of President Obama[18].

The influence of the number of background checks on the incidence of mass shootings also fails to reach statistical significance, but this might require further investigation, possibly on larger data sets. The feasibility of such an influence is indirectly supported by empirical research on state-level firearm-related murders[34]. Within a contagion model, the authors demonstrate a significant association between the prevalence of firearm ownership and the incidence of firearm-related murders collated from USA Today and the Brady Campaign to Prevent Gun Violence. Our approach could potentially be extended to study interactions between states with respect to firearm ownership and the occurrence of mass shootings, following recent evidence by Reeping et al. on a tenable dependence of the occurrence of mass shootings on state-level firearm restrictiveness and prevalence[35]. However, care should be placed in extending the information-theoretic approach to large ensembles of time series to ensure adequate statistical power[22]. Examining potential interactions between media coverage on firearm control policies and the incidence of mass shootings confirms our intuition that an influence is unlikely in either direction. Media coverage on firearm control policies does not help to predict the occurrence of a mass shooting. Similarly, variations in media coverage on firearm control policies are not explained by the occurrence of mass shootings, probably because not all incidents raise the same volume of media coverage on firearm control policies, although they may stimulate a similar volume of coverage on the mass shooting event. Previous studies have found that media coverage on mass shootings does result in changes in public opinion on gun control, but these changes are not always in the same direction. In 2000, a year after the Columbine High School mass shooting, a record high percentage of Americans (66%) approved of stricter firearm regulations, while the notable mass shooting in Newtown was followed by a decrease in public support for such regulations[36].

While our analysis favours the explanation that the fear of more restricted access to firearms is one of the leading drivers for people's tendency to seek the acquisition of a firearm, we cannot completely dismiss the explanation offered by Wallace[18], on the basis of appraisal theory[37]. Within appraisal theory, individuals' emotions are elicited by their subjective interpretation of an event, such that the reason for purchasing a firearm in the aftermath of a mass shooting is the desire for self-protection. In 2014, Chapman University (Orange, CA, USA) surveyed 1,500 people at random in the United States about their fears, and "being the victim of a mass/random shooting" was ranked fourth, according to ref. [38]. An equivalent survey conducted in 2017 documented that 28.1% of Americans are afraid or very afraid of "random mass shooting"[39]. As argued by Large, from *The Seattle Times*[38]: "Except for public speaking, the list [of Americans' top five fears] reflects the kinds of stories that have high profiles in the news, and they get airtime and big headlines because they are out of the ordinary. Cancer, heart disease and stroke are far more dangerous, but weren't at the top of the list."

However, our results all support the explanation that people seek firearms out of fear of more restricted access to them in the aftermath of a mass shooting. First, our analysis at the state level reveals that people in states with more relaxed policies responded more strongly to media coverage on firearm control policies. Second, we did not identify significant influence of media output on background checks when news documents included shootings but excluded firearm laws and regulations, indicating that self-protection alone is unlikely to fully explain subsequent firearm acquisition. Last, we failed to identify significant transfer entropy from media coverage on unemployment to background checks, after controlling for mass shootings. If people sought to acquire firearms for self-defence, in fear of violent crimes that mirror social disorganization, media coverage on unemployment should influence background checks, as the unemployment rate has been linked to violent crime through mechanisms such as a lack of social trust in communities[30].

The present study is not free of limitations in the process of data collection and analysis. With respect to the former, we identify the following four key drawbacks. First, the number of monthly background checks is only an approximation of the number of firearms that are actually purchased every month. As acknowledged by Wallace[18], a background check may not translate into an acquisition and not all purchases (illegal and legal) generate a background check. Second, the criteria for defining a mass shooting used by *Mother Jones*[20] exclude mass murders involving family members and criminal activities[40], which might also receive considerable media attention. Third, our analysis does not take into consideration either the number of people killed in the event or the characteristics of the victims, any of which could potentially influence media output[41]. Fourth, our data on media coverage on firearm control policies is limited to only two outlets (albeit among the largest in readership), due to a lack of available transcripts from other popular media for the entire observation period between 1999 and 2017. However, considering that television and radio often summarize news reported in these major newspapers, and both *The New York Times* and *The Washington Post* maintain extensive websites as well as social media presences, we believe that these two newspapers provide an important snapshot of the current national media content. Future work could utilize sentiment analysis to differentiate media coverage between pro-gun and anti-gun control messages and explore explanations for variations in the average time it takes for media reports to trigger increased background check activity. Last, it is important to note that the relationships identified here are likely to be specific to the US context. While other countries have certainly experienced mass shootings in recent years, the association between such events and fear of stronger firearm regulation might be uniquely American.

The key shortcomings of the proposed methodology are primarily due to the limited resolution and length of the available time series on background checks, which only includes 19 years of data at a monthly basis. With a monthly resolution, contemporaneous effects[42] might take place, in which the occurrence of a mass shooting could affect background checks within the same month. The use of a symbolic representation might partially compensate for these effects, in which a symbol in background checks or media output encapsulates a change between 2 months rather than an instantaneous value. With only 228 data points, it is difficult to go beyond a triad towards including additional variables[43], which might hamper the assumption of causal sufficiency at the core of information-theoretic approaches to the inference of causal links[42]. However, there is limited evidence in the public health literature about other factors that could mediate the relationship between mass shootings and firearm acquisition. In addition, the limited length of the time series challenges our ability to increase the number of symbols used in the representation of the time series[44], incorporate additional knowledge about past time series in the transfer entropy analysis[45], or explicitly treat seasonal effects[46] and trends in background check data, which were eliminated at the onset of the analysis to generate a stationary time series. Should more data become available, one could attempt estimating transfer entropy on a finer timescale, rather than aggregating it over the selected 19-year observation window. Despite these limitations, testing the robustness of inferences against ground-truth, synthetic data suggests that 19 years of data collection should suffice to pinpoint a true link from media output to background checks against the other false links.

Within a multivariate, information-theoretic approach to time series analysis, we have offered evidence in favour of the hypothesis that the fear of more stringent firearm control policies is an important driver for firearm acquisition. It is surprising to discover that this fear is probably unfounded: mass shootings have seldom been followed by new policies that restrict firearm acquisition[31]. On average, a mass shooting is followed by an approximately 15% increase in the number of newly introduced firearm-related bills, but the laws actually enacted have mostly loosened previous restrictions[31]. Future work should seek to account for this additional legal dimension, towards laying the foundations of a theory of the 'firearm ecosystem', in which individual decisions co-evolve with legal changes, shooting incidents and media coverage.

Methods

Data collection. Here, we describe the process that we have pursued for collating data on mass shootings, media output and background checks.

Background checks. There is no national registry or a complete record of gun acquisition in the United States. Hence, we used the monthly Federal weapons background check numbers as a proxy measure for gun acquisition on the FBI website[7]. The National Instant Criminal Background Check System (NICS) was mandated by the Brady Handgun Violence Prevention Act and was implemented in November 1998 by the FBI according to https://www.fbi.gov/services/cjis/nics/nics (accessed 15 November 2018). The system allows an authorized seller to instantaneously determine whether a prospective buyer is eligible to purchase a firearm. NICS data are widely used as a proxy for firearm acquisition[17,18,47]. Although the number of background checks does not necessarily correspond to the actual number of firearm acquisition, we removed any background checks for non-purchase purposes to obtain the best approximation possible from available data.

In our study, background checks were limited to handgun, long gun, other (referring to frames, receivers and other firearms that are not handguns or long guns) and multiple guns. Background checks associated with permit checks, pre-pawn, redemptions, rentals, private sales and returns to seller were excluded, as they should not lead to changes in national firearm prevalence. For our state-level analyses, we collected data for the 50 US states (see Supplementary Information), but excluded Connecticut and Hawaii from the analysis, as the available data seemed corrupted, with Connecticut registering almost 2 years of continuous zeros in the number of background checks and Hawaii always reporting zero background checks except for 1 month in nearly 20 years.

Mass shooting data. There are no comprehensive government data repositories on mass shootings in the United States. Hence, we used data compiled by a private organization. Specifically, we used the list compiled by *Mother Jones*, a US magazine that publishes on various topics, including politics and the environment. The database, found on the *Mother Jones* website[20], contains data from January 1982, but we only considered incidents from January 1999 to December 2017 due to the lack of NICS data before 1999.

Mother Jones has four main criteria for the inclusion of incidents to the mass shooting database[48]. First, excluding the shooter, at least four people died. This is based on the definition of mass murders by the FBI. Starting in 2013, the casualty threshold was changed to three or more killings to follow the definition of mass killings used by the US Congress[49]. Second, a lone shooter was responsible for the killings (except for the Columbine High School case and the West Middle School case). Third, the incident occurred in a public place, typically in a single location—although few instances included more than one location over a short period of time. Fourth, crimes related to gang activity or armed robbery are not included. The database provides details about the location; the date of occurrence; a summary of the shooting; the number of people injured and killed; the age, race, gender and mental health of the shooter; the type of weapon(s) used; how the weapons were obtained; and the news source for the mass shooting. We corrected the dates of two mass shootings (Seattle café shooting on 30 May 2012 and Trestle Trail bridge shooting on 3 May 2015) by manually cross-checking with several media reports, and the corrected data were used in the analysis. We must acknowledge that there are several definitions of mass shootings, as comprehensively discussed in the work by Duwe[50].

Media output. To characterize the effect of media coverage on firearm laws and regulations, we searched the ProQuest database. Specifically, we collected all documents with the subject heading "Firearm Laws and Regulations" in newspapers monthly from January 1999 to December 2017 and aggregated these into a single quantity, which we refer to as 'media output' (Fig. 1d). The analysis was restricted to *The New York Times* and *The Washington Post* due to their broad readership and availability of data covering the NICS data set (from 1980 onward). Transcripts from other popular media, such as CNN and Fox News, are unfortunately available only from October 2004 onwards, and were thus omitted from the analysis. To explore the effect of media coverage that is not associated with firearm control policies, we collected the documents with the subject heading "Shootings", excluding "Firearm Laws and Regulations" in newspapers in the same manner.

In addition, we collected documents in the same way described above but instead used the subject heading "unemployment" (Supplementary Fig. 14). The term was chosen to reflect news that lack direct association with mass shootings or background checks, but might potentially be linked to social disorganization and violent crime[30].

Information-theoretic framework. We adopt an information-theoretic framework to investigate the intertwined relationships between mass shootings, media output and background checks. Such an approach allows for a model-free treatment, which is robust with respect to non-linear interactions and multiple delays between the variables of interest. A comprehensive review of the mathematical concepts underpinning the proposed theoretical framework can be found in the book by Bossomaier et al.[22].

Within the field of information theory, information is "a measure of how much choice is involved in the selection of the event or of how uncertain we are of the outcome"[51]. In this vein, the entropy of a discrete random variable X is defined through

$$H(X) = -\sum_{x \epsilon \chi} \Pr(X=x) \log \Pr(X=x), \tag{1}$$

where $\Pr(\cdot)$ represents probability and x contains all of the possible realizations of X. By using a base two for the logarithm, entropy is naturally measured in bits. By construction, entropy in equation (1) is a non-negative quantity, which might be viewed as the expectation of the random variable $-\log\Pr(X=x)$. Null entropy corresponds to the case when X is a deterministic quantity. Conversely, the largest entropy is attained when X is uniform over its sample space; in this case, $H(X) = \log|\chi|$, where $|\chi|$ is the cardinality of the sample space.

By viewing entropy as the expectation (with a negative sign) of the logarithm of the probability mass function, it is natural to define the joint and conditional entropies for a pair of variables X and Y,

$$H(X, Y) = -\sum_{x \epsilon \chi,\, y \epsilon \Upsilon} \Pr(X=x, Y=y) \log \Pr(X=x, Y=y) \tag{2a}$$

$$H(X \mid Y) = -\sum_{x \epsilon \chi,\, y \epsilon \Upsilon} \Pr(X=x, Y=y) \log \Pr(X=x | Y=y) \tag{2b}$$

where, in general, the sample space of Y (Υ) is different from x. The joint entropy may be associated with the overall uncertainty of both random variables. Similarly, the conditional entropy of X given Y should be understood as the amount of uncertainty in X given knowledge about Y.

The notion of conditional entropy constitutes the foundations on which we can infer causal influence between time series in a Wiener–Granger sense. Given a pair of discrete-time stationary stochastic processes $X = \{X_t\}_{t\in\mathbb{N}}$ and $Y = \{Y_t\}_{t\in\mathbb{N}}$, we define transfer entropy from Y (source) to X (target) as ref. [21]

$$\mathrm{TE}_{Y\to X} = H(X_{t+1} \mid X_t) - H(X_{t+1} \mid X_t, Y_t) \tag{3}$$

Transfer entropy is a non-negative quantity that measures the reduction in the uncertainty of predicting the future value of X from its present, due to additional knowledge about the present of Y. If Y does not encode useful information that can help to predict the future of X, transfer entropy will be zero. Conversely, if knowledge of Y helps to improve our ability to predict X from its present, we record a positive quantity for transfer entropy.

When dealing with three processes, such as those examined in this paper, equation (3) should be expanded to account for the presence of a third stationary process. More specifically, given three stationary processes $X = \{X_t\}_{t\in\mathbb{N}}$, $Y = \{Y_t\}_{t\in\mathbb{N}}$ and $Z = \{Z_t\}_{t\in\mathbb{N}}$, we define conditional transfer entropy from Y to X, with Z being the conditioning process, as ref. [22]

$$\mathrm{TE}_{Y\to X|Z} = H(X_{t+1} \mid X_t, Z_t) - H(X_{t+1} \mid X_t, Y_t, Z_t) \tag{4}$$

Put simply, this quantity allows for controlling the effect of spurious interactions through Z by systematically conditioning the prediction of the future of X on the present of Z. For example, should Z act as a common driver for both X and Y, through equation (4), we would detect null conditional transfer entropy from Y to X, as Y will not encode meaningful information to help predict the future of X from its present and the present of Z. Just as we can control for the possibility of Z to act as a common driver, we can use equation (4) to discount cascade effects, in which Y will influence X only indirectly through Z. Also in this case, we would obtain null conditional transfer entropy, as Y will add no new knowledge to predict the future of X beyond what is offered by Z. With respect to our fundamental triad of mass shootings, media output and background checks, it is of particular importance to separate indirect and direct influences between them.

In its basic incarnation, conditional transfer entropy in equation (4) is computed by using a unitary time step. In a more general setting, one may consider delaying both Y and Z, using different time lags to evaluate the possibility of delayed interactions in the triplet. In the Supplementary Information, we consider this more general setting, along with an equivalent analysis conducted on pairwise interactions. The analysis confirms our intuition that a unitary time step in the information-theoretic analysis is sufficient to capture the dynamics of the triad.

From a practical point of view, conditional transfer entropy can be evaluated from empirical distributions of the processes, as estimated from their associated time series. Various methods can be pursued to undertake this task[22,52,53], but care should be placed in ensuring that the time series is sufficiently long to support proper estimation of all the pertinent probability mass functions. In our case in which only a few hundred data points are available, we address this challenge through a symbolic representation of the time series[44], as further detailed below.

Data preprocessing. The raw monthly background check data show clear seasonality and non-stationarity (Fig. 1a), which might hamper our ability to infer relationships with other variables or potentially lead to incorrect claims. More specifically, the proposed information-theoretic approach relies on the stationarity of the time series, which would be challenged by any underlying seasonal effect. Hence, the background check data were seasonally adjusted using the TRAMO/SEATS method.

The algorithms TRAMO and SEATS provide a complete model-based technique for signal extraction and forecasting. TRAMO/SEATS was chosen because of its ability to handle large irregular components better than other seasonal adjustment methods and packages[54]. We performed an automatic time series decomposition of the monthly background checks into seasonal, trend-cycle and irregular components, after which we generated the seasonally adjusted background check time series. In addition, the seasonally adjusted background check time series was linearly detrended so that the deterministic trends are removed (Fig. 1b). Following the seasonal adjusting and detrending, the augmented Dickey–Fuller test was run to ensure the stationarity of the new time series using a statistical significance value of 0.05. In addition, the same test was run for the occurrence of mass shootings and the media output, respectively, to check the stationarity. The analysis was implemented using the EViews statistical package.

To afford inferences over the available data set, a symbolic approach was chosen for the computation of conditional transfer entropy[44]. Symbolic representations are often used when a relative change in the time series rather than their magnitude is important[55]. For the time series of seasonally adjusted, detrended monthly background checks (BC) and monthly media output (MO), the change between 2 successive months was given a symbol '1' if the change was greater than zero and '0' if the change was less than or equal to zero. For the monthly mass shooting (MS) occurrence time series, a symbol '1' was given if one or more mass shooting occurred and '0' if no mass shooting had occurred during the month. Therefore, at a given time t, the triplet (BC_t, MS_t, MO_t) measures whether there was an increase or a decrease in the number of background checks (seasonally adjusted and detrended) from $t-1$ to t, a mass shooting took place at time t, and there was an increase or a decrease in the media output from $t-1$ to t.

Data analysis. To quantify potential associations between any pairs of variables (background checks, mass shootings and media output), a Kendall rank correlation test was performed. For any pair, the correlation coefficient (τ ranging from −1 to 1) and the P value were calculated to evaluate the strength of the relationship between the two variables.

Conditional transfer entropies were computed between all of the six possible combinations for the given triplet of time series. More specifically, we computed $\mathrm{TE}_{\mathrm{MS}\to\mathrm{BC}|\mathrm{MO}}$, $\mathrm{TE}_{\mathrm{BC}\to\mathrm{MS}|\mathrm{MO}}$, $\mathrm{TE}_{\mathrm{MO}\to\mathrm{BC}|\mathrm{MS}}$, $\mathrm{TE}_{\mathrm{BC}\to\mathrm{MO}|\mathrm{MS}}$, $\mathrm{TE}_{\mathrm{MO}\to\mathrm{MS}|\mathrm{BC}}$ and $\mathrm{TE}_{\mathrm{MS}\to\mathrm{MO}|\mathrm{BC}}$. Transfer entropy values were computed by first estimating the pertinent probability mass functions from the frequencies of occurrence of symbols and then evaluating the related joint entropies. To obtain the distribution of each of these transfer entropies under the null hypothesis that it is zero, we generated 50,000 surrogate symbolic time series following a local permutation scheme. For each of the 6 combinations, we obtained the empirical distribution over the 50,000 surrogate computations and utilized a significance level of 0.05 to verify whether the original values were in the right tail of the distribution (that is, a one-sided test). All conditional transfer entropy computations were performed using a custom-made code in Mathematica (see the 'Code availability' section).

The local permutation scheme is adapted from the approach presented by Runge for continuous time series[42]. For each combination of $\mathrm{TE}_{Y\to X|Z}$ in equation (4), the method implements the following two steps. First, we identify in the two-dimensional time series (X_t, Z_t), the times at which we register the pairs (0,0), (0,1), (1,0) and (1,1), and we collate them in four different subsets. Second, within each of these four subsets only, we randomly shuffle the time series Y_t to preserve the association between (X_t, Z_t) and Y_t.

The validity of the proposed approach was tested on synthetic binary data, generated through a first-order Markov chain, constructed on a priori known interactions within the triad. While mass shootings and media output evolved independently of any other variable, background checks in the synthetic data depended on media output. We generated time series of the same length of the observed data, and conditional entropies were computed for all six combinations between pairs in the triad (see Supplementary Information).

Furthermore, we performed conditional transfer entropy analysis for each US state. We computed transfer entropy from media output to state-level background checks (detrended and seasonally adjusted), conditioned on mass shootings in the same way for each state. The augmented Dickey–Fuller test indicates stationarity for the seasonally adjusted and detrended background check time series for all states ($P \le 0.046$ for all). To investigate whether the differences in the magnitude of transfer entropy among states were related to the variation in the climate of firearm-related policies among states, we quantified the restrictiveness of firearm-related laws in each state (excluding Connecticut and Hawaii) as a proportion of effective firearm-related laws out of the 133 laws (see Supplementary Information). The magnitudes of transfer entropy were fitted into a GLM with gamma errors and an inverse link, specifying the restrictiveness of firearm-related laws as an explanatory variable, weighted by the population of the corresponding state. Statistical significance was checked using a likelihood ratio test, comparing the model with a null model without the restrictiveness of firearm-related laws as an explanatory variable. Finally, we compared the restrictiveness of firearm-related laws between the states that registered significant transfer entropy from media output to background checks and those that did not, using a t-test (two-sided), weighted by the corresponding state's population.

A significance level of 0.05 was used for all analyses.

Reporting Summary. Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability

All data needed to evaluate the paper's conclusions are presented in the article and the Supplementary Information, as well as being freely available at https://github.com/Causality-Research/Firearms.

Code availability

The code used to reproduce the results is freely available at https://github.com/Causality-Research/Firearms.

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Author contributions
S.N. and M.P. designed the research. R.R.S. collected the data. All authors contributed to the formulation of the hypotheses underlying the study. S.N., M.P., R.R.S. and R.S. conducted the analysis. M.P. wrote the first draft of the manuscript. All authors discussed the results and edited the final version of the manuscript.

Competing interests
The authors declare no competing interests.

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Study description	The study presents quantitative analysis of longitudinal data.
Research sample	The study used publicly available data in the U.S.
Sampling strategy	We collected all monthly data from 1999 to 2017.
Data collection	Background checks data were collected from the NICS website, and mass shootings data were collected from Mother Jones website. Media output were collected using Proquest database.
Timing	We collected all monthly data from 1999 to 2017.
Data exclusions	Background checks data of Hawaii and Connecticut were excluded from the analysis due to data corruption.
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