The TikTok effect: causal roles of public opinion in firearm acquisition

Andalib Samandari*, Kevin Slote*; Advisors: Dr. Igor Belykh*, Dr. Maurizio Porfiri**

*Georgia State University, **New York University

Abstract

We explore the causal effect of public opinion on gun purchases. Previous work found Twitter posts by anti-regulatory organizations drive gun purchases, proxied by NICS firearm background checks [1]. Here we examine TikTok videos (TikToks), capturing a younger and more general audience. We performed a pilot study to collect and transcribe TikToks about #guncontrol, and performed zero-shot text classification to obtain separate time series of pro- and anti-regulation content. We then performed a statistical causal analysis between this TikTok discourse and background checks using the PCMCI framework. The result is a causal network quantifying the interplay between pro- and anti-regulation TikToks and how they drive firearm purchases in the United States.

Zero-shot text classification

To classify our sample of 3,436 TikToks, we used zero-shot classification, where a deep learning model is trained on a set of labeled text examples, and then used to classify new examples in previously unseen classes. Models based on the transformer architecture, such as large language models, are particularly effective for zero-shot classification [2][3].

We used the 407 million parameter transformer model `bart-large-mnli` from Facebook, without any fine-tuning. Classification steps were:

1. Transcribe the TikTok audio using the Google Cloud Speech API, then combine the transcription with the description text and hashtags to obtain a text representation of the video.
2. Create three categories for the data: "opposed to gun regulation", "in favor of gun regulation", and "undefined". The inclusion of a null category is to avoid forced classification with low confidence.
3. Use Hugging Face pipelines to pass each text row to bart-large-mnli, and assign a category based on the highest score returned by the classifier.

PCMCI causal discovery framework

For the causal analysis we used the PCMCI algorithm with the software package Tigramite [4]. PCMCI begins with a complete time series graph G, where each node X_t^n represents the time series of a variable at a certain time lag. 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 lag 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 lag tested for in the algorithm. The algorithm is based on a variant of the PC algorithm [5] and the concept of momentary conditional independence (MCI) inspired by the information-theoretic measure of momentary information transfer [6]. 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 converges, links are oriented based on time delays; that is, if a link exists between X_{t1}^i and X_{t2}^j, the orientation of the link between i and j is posed based on the difference between $t1$ and $t2$ ($i \rightarrow j$ if $t1 < t2$, $j \rightarrow i$ if $t2 < t1$, and $i - j$ if $t1 = t2$). 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. (From [1] by Daley, Slote et al.)

Results

We aggregated the TikTok data by day, and created time-series plots for anti-regulation and pro-regulation videos as well as background checks, shown in **Figure 1**. Some notable features of each time series are highlighted with plausibly related world events.

We deseasonalized the time series for daily, weekly, monthly and quarterly seasonality, then PCMCI with a lag of up to 7 days and a significance level of 0.05. A diagram of the resultant causal network is in **Figure 2**, along with average mutual information in **Table 1**.

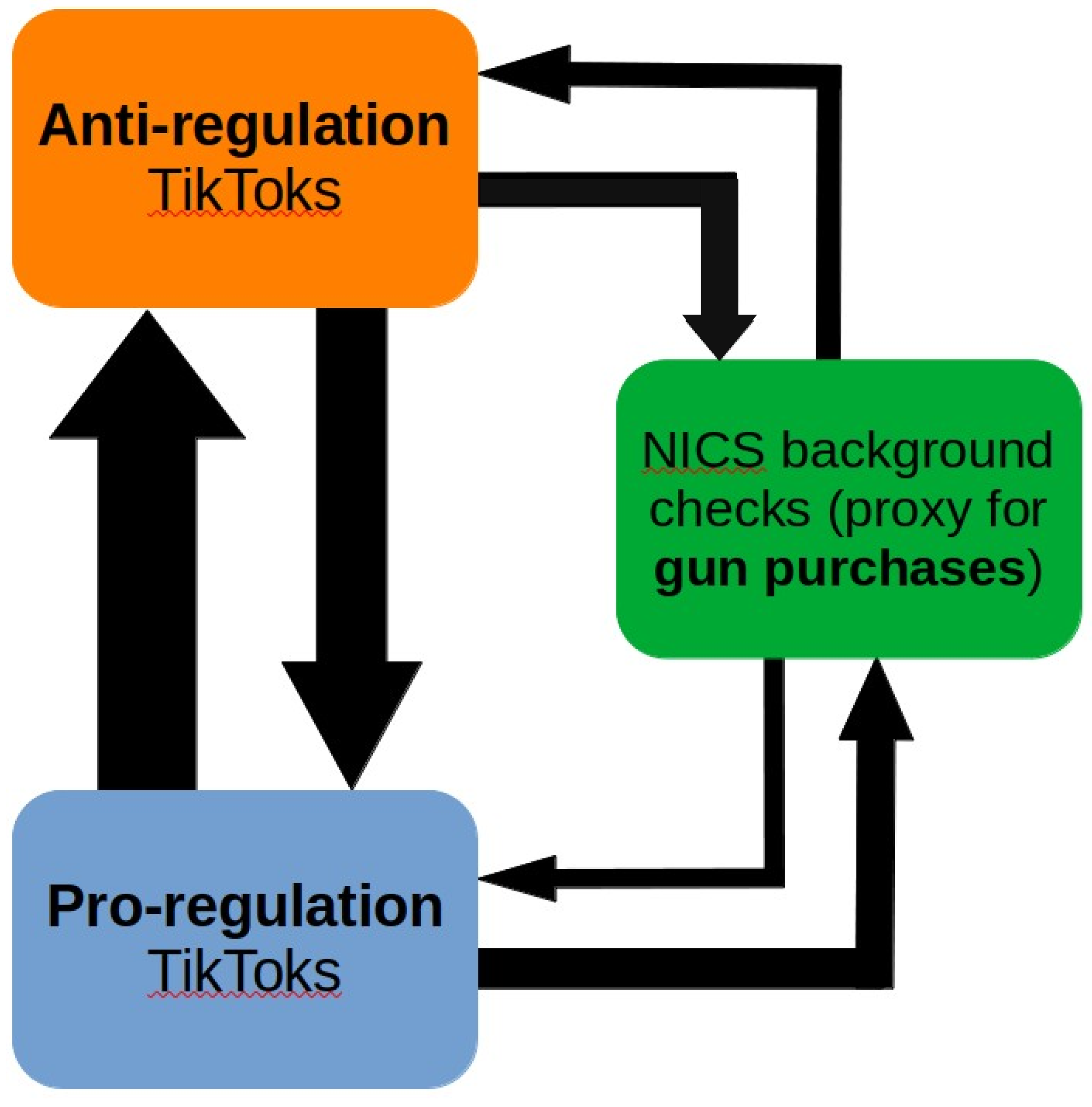

Figure 2 The causal network discovered by the PCMCI algorithm, lag 0-7 days. Wider arrows represent a stronger causal influence. Average uni-directional mutual information values are in **Table 1**, all with a p-value of 0.01 or less.

Table 1 Average mutual information values for the links shown in **Figure 1**. All have a p-value of 0.01 or less.

Source	Destination	Average mutual information (nats)
Background checks	Anti-regulation TIkToks	0.0889
Background checks	Pro-regulation TIkToks	0.0690
Anti-regulation TIkToks	Background checks	0.0951
Anti-regulation TIkToks	Pro-regulation TIkToks	0.0792
Pro-regulation TIkToks	Background checks	0.0839
Pro-regulation TIkToks	Anti-regulation TIkToks	0.1521

Discussion

There are several implications of these findings to be verified in future work. TikTokers on different sides of the discourse respond to each other, shown above as a bidirectional link between TikTok categories. The link from gun purchases (proxied by background checks) to both kinds of TikToks could be explained by gun purchases being correlated with firearm-related events and headlines, which are often the subject of TikTok content on gun control. A more suprising finding is that pro-regulation TikToks also drive purchases, not only anti-regulation posts. This could be evidence for reactionary gun purchases due to fear of regulation (as in [7] and [8]).

Conclusion

This work adds further evidence in line with a prior study [1] that public opinion and social media posts drive gun purchases. In particular, our results support a theory of reactionary behavior, not only online but in real life, where gun purchases are driven by fear of regulation. Given that TikTok caters to a younger generation, we can expand these results to further quantify the effect of Gen Z opinion on firearm purchases, and uncover the causal interplay between social media discourse and news media coverage on firearms as in our Twitter study.

References

[1] Daley, K., Slote, K., Succar, R., Ventura, R. B., Porfiri, M., & Belykh, I. (2020). *How Anti-Regulation Organizations Drive Firearm Acquisition in the United States: Analysis within a Causal Inference Framework.*
[2] Chae, Y., & Davidson, T. (2023). *Large Language Models for Text Classification: From Zero-Shot Learning to Fine-Tuning.* https://doi.org/10.31235/osf.io/sthwk
[3] Schopf, T., Braun, D., & Matthes, F. (2022). Evaluating unsupervised text classification: Zero-shot and similarity-based approaches. *Proceedings of the 2022 6th International Conference on Natural Language Processing and Information Retrieval.* https://doi.org/10.1145/3582768.3582795
[4] Jakob Runge. Discovering contemporaneous and lagged causal relations in autocorrelated nonlinear time series datasets. Conference on Uncertainty in Artificial Intelligence, 1388–1397. PMLR, 2020.
[5] Peter Spirtes and Clark Glymour. An algorithm for fast recovery of sparse causal graphs. *Social Science Computer Review*; 9(1):62–72, 1991.
[6] Jakob Runge, Jobst Heitzig, Norbert Marwan, and Jurgen Kurths. Quantifying causal coupling strength: A lag-specific measure for multivariate time series related to transfer entropy. *Physical Review E*; 86(6):061121, 2012.
[7] Porfiri, M., Barak-Ventura, R., & Marín, M. R. (2020). Self-protection versus fear of stricter firearm regulations: Examining the drivers of firearm acquisitions in the aftermath of a mass shooting. Patterns, 1(6), 100082. https://doi.org/10.1016/j.patter.2020.100082
[8] Pierre, J. M. (2019). The psychology of guns: Risk, fear, and motivated reasoning. Palgrave Communications, 5(1). https://doi.org/10.1057/s41599-019-0373-z

Acknowledgements

Thank you to Kevin Slote for gathering the TikTok data, and for his support in carrying out the tests. I am also grateful to Dr. Belykh, Dr. Porfiri and the LEAP-HI firearm research group for their mentorship. And thanks to the LSAMP Fellowship for sponsoring me again this year, and to the NSF grant (no. CMMI-1953135) supporting the Belykh Lab at GSU.

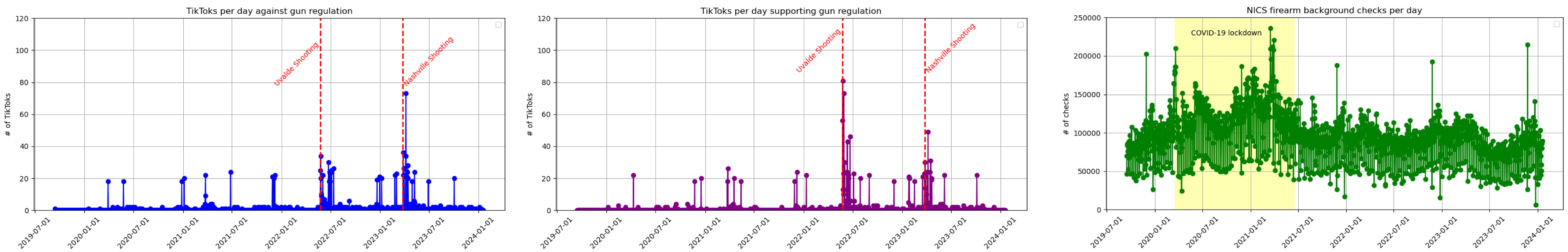

Figure 1 Daily time series plots for (left to right): anti-regulation TikToks, pro-regulation TikToks, and NICS firearm background checks between 2019-09-15 and 2024-01-19.