Formative reasons for state-to-state influences on firearm acquisition in the U.S.

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ABSTRACT

Objectives: Firearm-related crimes and self-inflicted harms pose a significant threat to the safety and well-being of Americans. Investigation of firearm prevalence in the United States (U.S.) has therefore been a center of attention. A critical aspect in this endeavor is to explain whether there are identifiable patterns in firearm acquisition.
Methods: We view firearm acquisition patterning as a spatio-temporal dynamical system distributed across U.S. states that co-evolves with crime rates, political ideology, income levels, population, and the legal environment. We leverage transfer entropy and exponential random graph models along with publicly available data, to statistically reveal the formative factors in how each state's temporal patterning of firearm acquisition influences other states.
Results: Results help to explain how and why U.S. states influence each other in their firearm acquisition. We establish that state-to-state influences, or lack thereof, in firearm acquisition patterning are explained by states' percent of gun homicide, firearm law strictness, geographic neighborhood, and citizen ideology. Network-based characteristics, namely, mutuality and transitivity, are also important to explain such influence.
Conclusions: Results suggest that state policies or programs that reduce gun homicides will also help suppress that state's influence on the patterning of firearm acquisition in other states. Furthermore, states with stricter firearm laws are more likely to influence firearm acquisition in other states, but are themselves shielded from the effects of other states' firearm acquisition patterns. These results inform future research in public health, criminology, and policy making.

Keywords: firearm acquisition, state-to-state networks, causal influence, transfer entropy, exponential-family random graph models

1 INTRODUCTION

Firearm-related harms in the U.S. are a major public health problem, and the severity of this threat continues to rise. A sharp increase in gun homicide is observed in recent years (Gramlich, 2023); in 2021 alone, 20,958 people lost their lives due to assaults with firearms (Centers for Disease Control and Prevention, n.d.). According to the FBI, Americans faced a 33% increase in active shooter incidents from 2019 to 2020 and a 53% increase from 2020 to 2021 (Federal Bureau of Investigation, 2022). Strikingly, firearms are now the major cause of death for children and teens (Freedom du Lac, Josh, 2023). These problems are further exacerbated by self-inflicted harms; on 2010 data, Grinshteyn and Hemenway (2016) reveal that the U.S. has an eight-times higher rate of firearm-related suicides than other high-income countries. Firearm-related harms also bring about profound problems to the public, including mental health, behavioral impact on victims, and a high burden of medical care-related costs (Hemenway & Nelson, 2020; Leibbrand et al., 2020).

The complex interplay between firearm-related harms and the prevalence of firearms is underscored in the literature. Based on a causal analysis, Kovandzic et al. (2013) explain how gun restrictions do not necessarily reduce firearm-related crime rates. This may be because such restrictions can have little effect on reducing crimes while suppressing noncriminal gun prevalence - a potential deterrent of crimes. Kleck (2015) reviews the landscape of firearm research, pointing out that there may exist a link between firearm-related crime rates and firearm prevalence. Andrade et al. (2020) reveal that more restrictive state firearm laws may paradoxically help to stimulate gun trafficking networks resulting in the movement of illegal firearms from less restrictive to more restrictive states. Overall, there is strong interest in the community toward better understanding the reasons behind the patterning of firearm acquisition in the U.S.

Firearm acquisition is thought to be driven by a variety of factors, including the desire for self-protection, affinity for hunting, interests in recreational shooting, as well as culture, family traditions, and hobbying (Gallup Corporation, n.d.). A complex relationship also exists between firearm ownership and social/political life in America: firearm ownership has become, to some degree, an indicator of political affiliation and social identity (Dowd-Arrow et al., 2019; Kalesan et al., 2016; Lacombe, 2019). To improve the understanding of firearm acquisition patterning in the U.S., it is also critical to consider both geographic (Azrael et al., 2004) and macro-level factors, such as firearm acquisition trends, firearm-related crimes, and relevant socioeconomic metrics (Kleck & Patterson, 1993; Porfiri et al., 2019).

U.S. states influence each other in many ways, including competition to attract businesses (Aguiar-Conraria et al., 2017), housing markets (Sheng et al., 2021), and public policy diffusion (Grabow et al., 2016). Hence, it is plausible that firearm acquisition patterning in one state affects firearm acquisition patterning in another state. For example, Porfiri et al. (2020) identified that firearm acquisition in one state can be predicted by the aggregated dynamics of firearm acquisition from its surrounding neighboring states. Macinko et al. (2023) reveal that background checks as a proxy of demand/support for firearms in one state is a critical parameter in policy diffusion process. Such policies can, in turn, influence local firearm ownership (Goldstein & Prater, 2022), as well as state firearm exportation rate from one state (Everytown Research & Policy, 2018). Kaufman et al. (2018) show that states with stronger firearm regulation contribute to reduced firearm homicide and suicide rates in neighboring states. This knowledge, combined with links between regulation, firearm acquisition, and firearm homicides/suicides (Anestis et al., 2021; Kposowa et al., 2016; Siegel et al., 2013), suggests state-to-state influences on firearm acquisition patterning. Furthermore, since guns as well as crime guns can be transferred across states (Collins et al., 2017; Webster et al., 2001), firearm acquisition in one state can influence that of another state through its impact on firearm prevalence as well as firearm safety.

In this manuscript, we understand that dynamics $\mathcal{S}_1$ 'influences' dynamics $\mathcal{S}_2$ if knowledge of $\mathcal{S}_1$ at time t improves our prediction of how $\mathcal{S}_2$ will behave from time t to $t+1$. This type of influence can be detected by statistical inferences. One popular technique, based on the Wiener-Granger concept of causality, is through the use of transfer entropy (TE) – a model-free approach that can help 'infer' the relative effect of one dynamical system on another, given their time series (Schreiber, 2000). This approach, especially in research areas where an underlying mathematical model is missing, has been instrumental in deciphering complex dynamical systems, such as detecting lead-follow relationships between animals and estimating the leadership capacity of specific individuals (Pilkiewicz et al., 2020). We propose to leverage TE to reveal how states influence each other in their firearm acquisition patterning. Such an influence may arise by various mechanisms as reviewed above, for example when two states through policy diffusion share similar firearm-related laws (Butz et al., 2015). This is however different from state-to-state interactions due to gun trades and gun trafficking across state borders, which are left outside the scope of our presentation.

Access to rich, multi-dimensional data is critical. Except for firearm sales, all other data are publicly available. We utilize state-level national instant criminal background check (BC) data as a proxy of firearm sales. This practice has been extensively pursued in the literature (Boine et al., 2020; Porfiri et al., 2020; Porfiri et al., 2019; Schleimer et al., 2021; Timsina et al., 2020) as it provides reliable means to support the link between BC data and firearm sales. For example, Boine et al. (2020) conduct a principal component analysis and found positive relations between the number of BCs for long-gun sales and state variables related to the usage of firearms for recreational purposes. The number of BCs for handgun sales were however found to be associated more with self-defense. Porfiri et al. (2019) study the BC data and detected fear of stricter firearm regulation as one driving factor of firearm purchases. In (Wang et al., 2022), the state-level analysis of BC data reveals the degree of synchronization among U.S. states and how it varies with respect to the terms of U.S. Presidents.

Previous studies linked various factors to firearm acquisition. For example, through the examination of state-level data sets about various gun-related behaviors, Boine et al. (2020) identify three elements (recreational, self-defense, and symbolic/cultural) underlying gun culture in different states. Likewise, Liu and Wiebe (2019) demonstrate significant association between major mass shootings and gun purchases through time-series analysis. Porfiri et al. (2019) show that fear of stricter firearm regulation is an important reason for gun purchases. Andrade et al. (2020) reveal the critical effect of firearm laws, state population and geographical distance in shaping state network structure for interstate firearm trafficking. Furthermore, by analyzing characteristics of participants in a gun-related survey conducted in 2018, Kelley and Ellison (2021) find participants with conservative leaning in political ideology are more likely to be future gun owners by anticipation, different from those with liberal leaning. Cook et al. (2011) note a positive association between gun ownership and income level when depicting the demographics of gun owners. Porfiri et al. (2020) point out that spatial proximity, or geographical neighborhood among the states is another factor that can explain their coupling in collective behaviors of firearm acquisition.

In view of the above discussions, it is of strong interest to investigate *how* states influence each other in their firearm acquisition patterning and *what are the formative reasons* for such influences. This is however not a trivial task given the heterogeneity of U.S. states in terms of gun laws, political and economic landscape, household income, and political ideology. Here, we address these questions through the lens of dynamical systems, whereby we view U.S. states as nodes of a network, whose relevant characteristics evolve over time. We take an approach that fuses information theory, network science, and statistical modeling, with available data in the public domain. We articulate the approach in two sequential steps. First, we utilize BC data to detect the influence of a state on another based on TE. This effort yields a network with directed 'ties' that indicate the direction of influence from a state to another. Second, starting from this network structure, we investigate the formative factors explaining these ties. Motivated by the literature review, we propose the following state-level attributes as candidate formative reasons: percent of gun homicide, median household income, population, firearm law strictness, citizen ideology, and geographic neighborhood (Clark et al., 2022; Desmarais et al., 2015; Shipan & Volden, 2012). These factors are next incorporated into the modeling phase of our work, where we build statistical models that can provide, with statistical significance, whether or not a tie from one state to another is more likely to arise in the presence of a particular factor. This is a challenging modeling problem with multiple factors and numerous possibilities of ties in the network, as well as potential inter-dependencies between the ties. One promising direction is to leverage exponential-family random graph models (ERGMs), which have been successfully implemented in various domains (Harris, 2013; Robins et al., 2007; van der Pol, 2019).

Researchers apply ERGMs in neuroscience to study connectivity networks of different brain regions (Simpson et al., 2011), in biology to detail metabolic networks of interactions between enzymes (Saul & Filkov, 2007), in tourism to examine networks of visit co-occurrence between tourist attractions (Hernández et al., 2021), in animal behavior to elucidate social structures (Ilany et al., 2013; Silk & Fisher, 2017), and in social science to explain adolescent friendships (Goodreau et al., 2009). Moreover, ERGM is applied in studies related to firearms, especially when it comes to studying state-level interactions at the network level. Andrade et al. (2020) make use of ERGMs to illustrate formation of a network of U.S. states associated with illegal firearm flows. They reveal that firearm regulation promotes the formation of networks of illegal firearm flows, from states with weaker gun laws to states with stricter gun laws. In terms of firearm laws, Clark et al. (2022) create an ERGM to interpret the driving factors for the dynamics of law adoption activities in different states, considering a bipartite network of state-law adoption relations.

ERGMs have the advantage that they do not rely on the important assumption of statistical independence, which aligns well with many real world social networks with strong dependence between their ties (Harris, 2013; Robins et al., 2007). However, by the nature of their mathematical construct, they can only provide a snapshot of how likely ties may form between the dyads, hence they are not suitable for studying dynamical changes over time. Nevertheless, ERGMs provide a promising foundation to allow for dyadic dependence with proper model terms, such as transitivity (the tendency of forming triangles) and mutuality (the tendency of forming reciprocated ties) found in social networks (Harris, 2013). An ERGM is similar to a binary logistic regression, but, differently, it conditions on the rest of the network graph when interpreting the probability of the presence of a tie in the network. Both the state-level attributes of any two nodes (for example, percent of gun homicide) and relevant network structural factors (for example, transitivity) can be used to formulate model statistics in ERGM to predict the probability that a tie exists between these two nodes. For these reasons, ERGMs offer an ideal modeling framework to explain what formative factors are more likely to establish ties between U.S. states.

The manuscript is organized as follows. The data used in this work is described in Section 2. The main methods and mathematical procedures are expanded in Section 3. Therein, we first illustrate the process of network inference through TE computations (Section 3.1) and then we address the identification of formative reasons of network of influence through the use of ERGMs (Section 3.2). Results from both mathematical endeavors are presented in Section 4. Interpretation of our results, limitations of the study, and main conclusions follow in Section 5. Supporting information can be found in the Appendix.

2 DATA

Public national instant criminal background check (BC) data (Federal Bureau of Investigation, n.d.) are utilized for analysis. This data is available at a monthly resolution, but it is not available for Hawaii. Hence, Hawaii is excluded from our study. Although the state of Connecticut has missing data from 1/2000 to 8/2001, this state is still included by considering zero values in place of the missing data. The time range of BC selected in this manuscript is from 1/1999 to 12/2017, corresponding to 228 months, or data points, in total.

In addition, we consider annual time series for percent of gun homicide, median household income, population, firearm law strictness, and citizen ideology as defined below.

Percent of gun homicide (PGH) The homicide data from CDC Wonder (Centers for Disease Control and Prevention, n.d.) is a state-level count of death, utilized in this manuscript with an annual resolution. This data is collected based on death certificates of U.S. residents from the National Center of Health and Statistics. The count of all homicides is filtered by the underlying cause of death 'Assault' from all death cases, based on ICD-10 codes from the death certificate. Counts of gun homicide is further narrowed down to deaths due to 'Assault by handgun discharge', 'Assault by rifle, shotgun and larger firearm discharge', or 'Assault by other and unspecified firearm discharge'. State-level homicide ratios are defined as the ratio of gun homicide to all homicides and is used as a unit-free indicator of prevalence of firearm-related crimes.

Median household income (MHI) MHI is an annual, state level measure derived from collected samples in Current Population Survey, 1985 to 2023 Annual Social and Economic Supplements ([dataset] U.S. Census Bureau, 2023). Based on the distribution of household income of survey samples in multiple income intervals, the median household income in the study time range is estimated using linear interpolation, assuming the population density in an income interval is constant. Furthermore, MHI is adjusted against inflation.

Population (PPL) PPL an annual estimation of a state from U.S. Census Bureau ([dataset] U.S. Census Bureau, n.d.). The Census Bureau estimates the time series of state population size using the cohort-component method, which means the population estimate starts from a population base from most recent decennial census results and fluctuates according to current birth rate, death rate, and net migration at a given time.

Firearm law strictness (FLS) State-level firearm law strictness is based on State Firearm Law Database from RAND Corporation ([dataset] Cherney et al., 2022). In this dataset, historic records of legislative actions (enactment, repeal and modification of a firearm-related law) for each state are listed. Firearm laws are classified as 'permissive' or 'restrictive', which means respectively the law will widen, or limit certain aspect of firearm access and usage. For the measure of firearm law strictness for one state in a year, we use its historic accumulated counts of enactment and modification of 'restrictive' firearm laws in this state till the end of this year.

Citizen ideology (CTI) Citizen ideology ([dataset] Fording, n.d.) for each state can show the characteristics of public orientation in a state's political culture, conservative or liberal, and ranges from a score of 0 (the most conservative) to 100 (the most liberal). Citizen ideology in one district at one year is reflected by combining the election results for Congress and the identified ideology positions of the incumbent and the challenger in the election. The state-level measure is merely an unweighted average of the same measurement in all the districts of the respective state. Citizen ideology is a validated measure frequently used in political

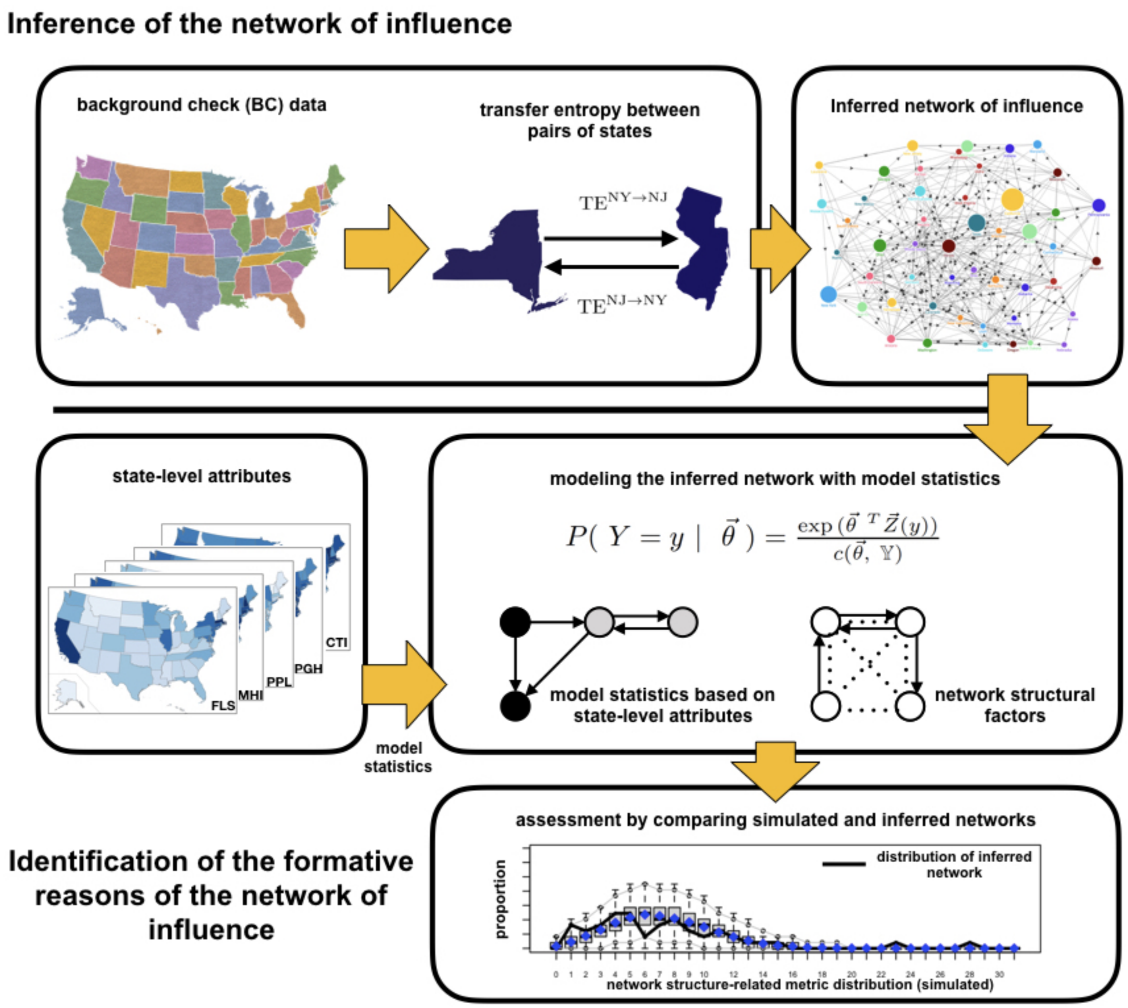


Figure 1: Overall sketch of the sequential steps of methodology pursued in this manuscript: we process raw BC data, compute TE values, construct a network of influence, and fit ERGMs to explain the network of influence from state-level attributes and network structural factors.

science studies.

These time series are over the same time span of BC data, except for ideology that ends in 2016.

3 METHODS AND ANALYSIS

We apply transfer entropy (TE) to infer which state influences which other state, based on the BC data. This study reveals a network of influence, which combined with ERGM and 'candidate formative factors', helps reveal the most critical factors explaining why ties form between states due to influences between them in their BC data. The approach contains two sequential steps: we first present the implementation of TE on BC data for constructing a network of influence and, then we present the application of ERGM on this inferred network. The content of each step is summarized in Fig 1.

3.1 Inference of the network of influence

The network of influence is inferred in two sub-steps: first, we compute TE between each pair of states using pre-processed BC data, and, second, we implement a threshold on TE values to infer the network of influence y^* based on relatively high TE values. Details on these two sub-steps are provided in Appendix 6.1.

3.2 Formative reasons of ties in y^*

Our approach to elucidate the formative reasons of ties in y^* is based on statistical modeling, leveraging ERGMs. To this end, we generate covariates based on a set of 'candidate' formative reasons. Through ERGMs, we estimate statistically which of the covariates indeed inform the existence/absence of ties in y^*. In this manuscript, we use 'tie' and 'edge' interchangeably, to be consistent with the usage of these terms in their respective literature (social networks versus network theory).

Let us denote by $\vec{Z}$ the vector whose entries are model statistics (see Appendix 6.2.1 where we detail how these model statistics are formulated based on covariates). These statistics are to be calculated for a given network y, where y is a realization of random network Y. In other words, entries in $\vec{Z}$ are functions of y, namely, model statistics associated with the nodes and node-to-node relationships. Hence, we can write $\vec{Z}(y) \in \mathbb{R}^p$, where p is the number of model statistics being considered. Furthermore, we account for a vector of scalar parameters $\vec{\theta} \in \mathbb{R}^p$ that encapsulates the weights associated with each covariate in $\vec{Z}(y)$ (see Appendix 6.3 for interpretations of $\vec{\theta}$). The probability distribution of Y within the ERGM framework is expressed as

$$P(\ Y = y \mid \ \vec{\theta}\ ) = \frac{\exp(\vec{\theta}^{\,T}\vec{Z}(y))}{c(\vec{\theta},\ \mathbb{Y})}, \tag{1}$$

$$c(\vec{\theta},\ \mathbb{Y}) = \sum_{y \in \mathbb{Y}} \exp(\vec{\theta}^{\,T}\vec{Z}(y)). \tag{2}$$

Here, $\mathbb{Y}$ is the sample space of unweighted directed networks expressed as $\mathbb{Y} = \{l \in \mathbb{R}^{n\times n} | \forall i, j\ l_{ii} = 0, l_{ij} \in \{0, 1\}\}$, and $c(\vec{\theta},\ \mathbb{Y})$ normalizes the probability to the range $[0, 1]$.

Inferred network y^* is next predicted using the above model. Specifically, a Markov Chain Monte Carlo maximum likelihood estimation (MCMC MLE) (Hunter & Handcock, 2006) is conducted with STATNET suite package (Goodreau et al., 2008) in *R*, to fit model (1) to y^*. In this fitting process, the goal is to maximize the log-likelihood of (1), which ultimately renders the estimates of the parameters in $\vec{\theta}$. Those parameters, if any, that significantly improve ERGM's prediction of y^* are identified as formative reasons of ties in y^*. With this mathematical procedure established, one can build different ERGMs with various model statistics and compare these models in terms of how well they predict y^* using the Akaike information criterion (AIC) (Stoica & Selen, 2004). Details on how the model statistics in $\vec{Z}(y)$ are set up and how the quality of model fitting is assessed can be found in Appendix 6.2.

4 RESULTS

We first present results on the topology of the network of influence among U.S. states, highlighting with an example how a state may have a key role in influencing a large part of the country. Then, we detail formative reasons underpinning the inferred influences based on the ERGM. We conclude the section with a goodness-of-fit analysis.

4.1 Inferred U.S. state network of influence in firearm acquisition

Based on the two sub-steps in Section 3.1, we infer the network of influence among U.S. states in terms of firearm acquisition, see Fig. 2. This is a network with edge density approximately 15% and each state is represented by a solid circle. A directed edge from state $\mathcal{S}_1$ to state $\mathcal{S}_2$ indicates that $\mathcal{S}_1$influences $\mathcal{S}_2$ in its firearm acquisition, and the size of each circle indicates the average estimated population of the state over the time span of the data.

The network of influence presents a complicated structure of relationships, which, at a first sight, is opaque to any interpretation. To this end, we inspect several states to interpret their role in the network of influence. Specifically, we examine Alaska (AK), Florida (FL), Georgia (GA), Illinois (IL), Massachusetts (MA), and Oregon (OR). We plot the ties of these states in separate panels in Fig. 3. We observe that AK, GA, MA, and OR all have a relatively small number of edges, showing a limited set of interactions with the rest of the country. However, AK and OR have mostly incoming edges indicating that these states are most often affected by other states. Interestingly, we do not detect any incoming edges to MA, indicating a degree of shielding from the rest of the country. Differently, IL has more outgoing than incoming edges, and it has a large number of connections to the whole country. Although FL and GA have fewer outgoing edges than IL, they still have a strong capacity in influencing other states because the number of their outgoing edges outnumber the number of their incoming edges.

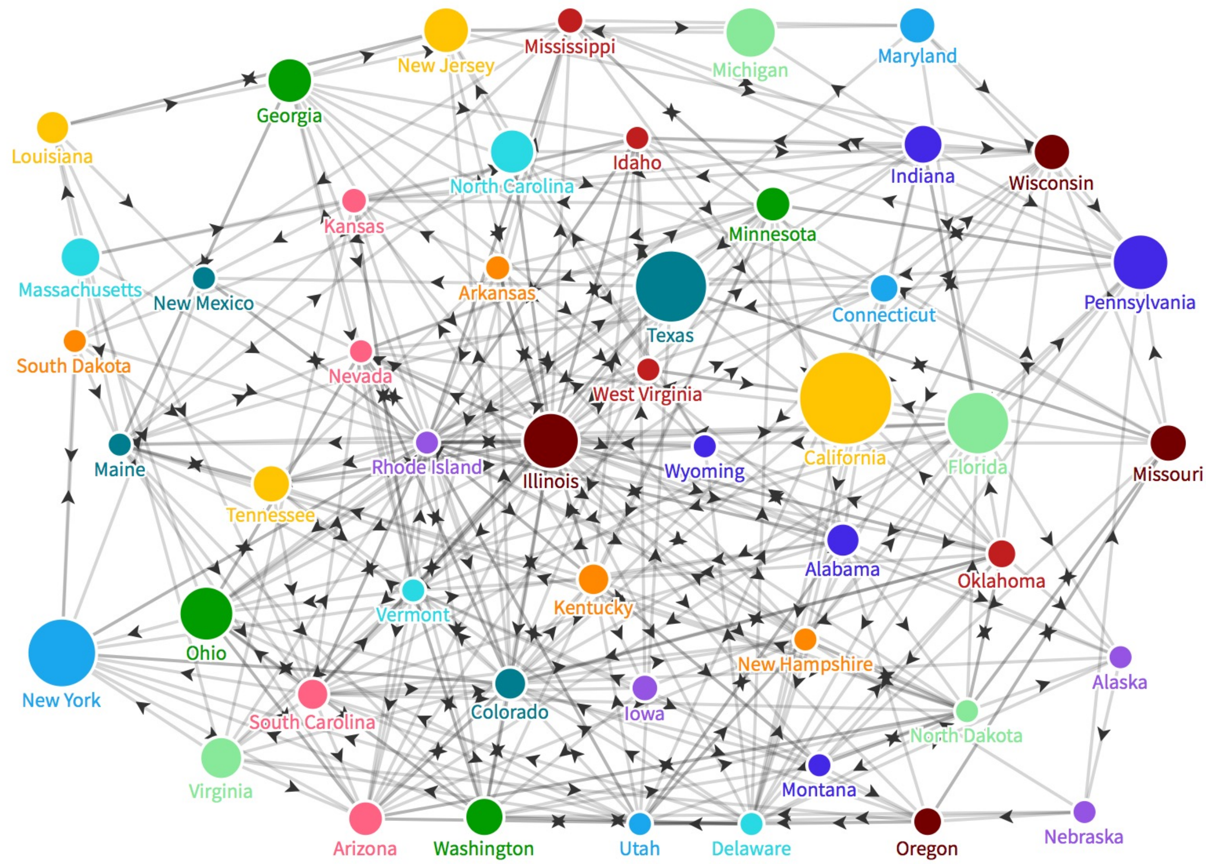
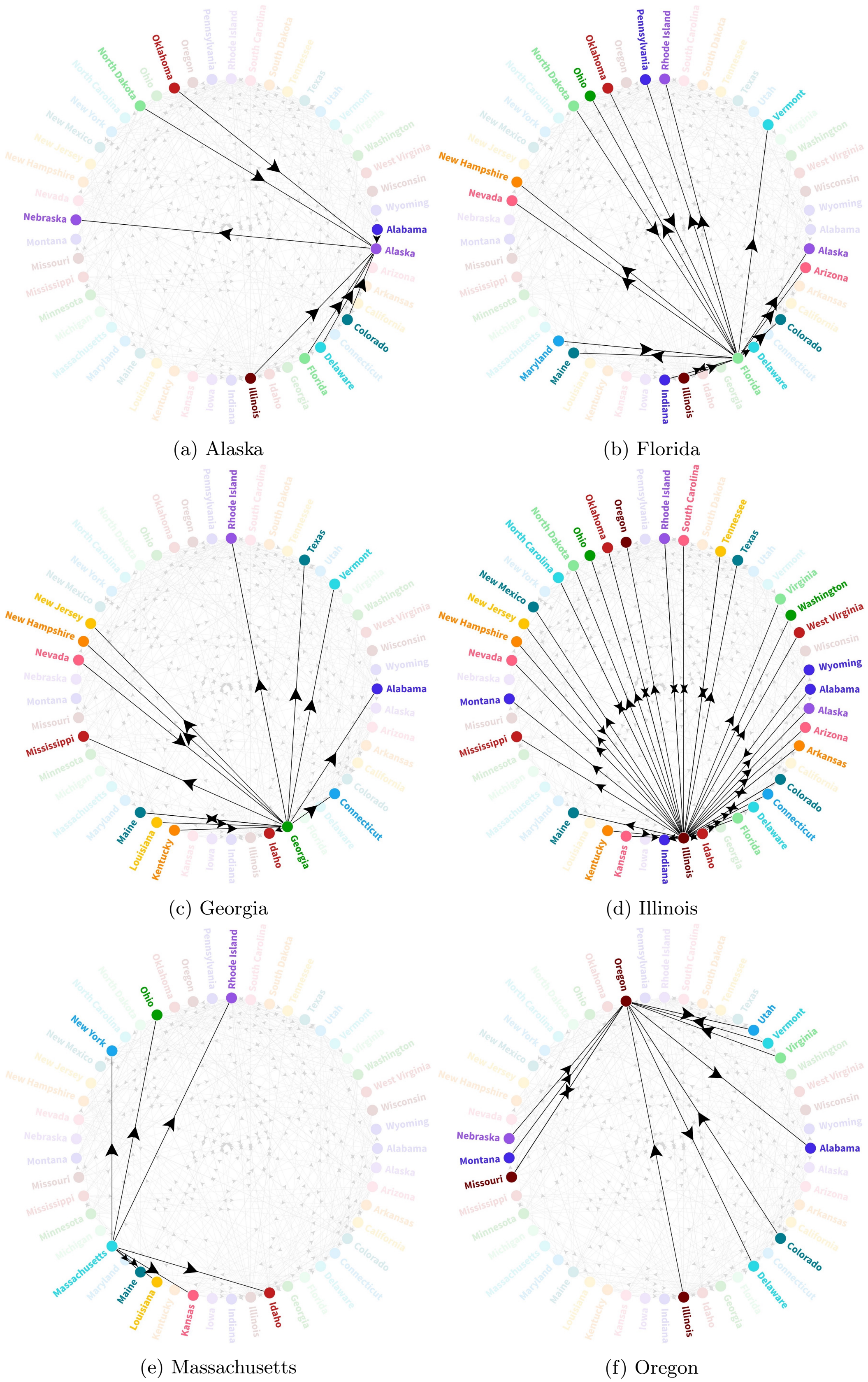


Figure 2: Inferred network of influence y^*. Circles represent U.S. states and arrows represent causal influence. The size of each node represents the state average population over the studied time range.

The interaction network provides information about which states are more likely to influence or be influenced by others, however, it does not explain why such interactions arise. For example, FL interacts with MD despite their geographic distance and wide differences in political ideology as measured by Berry et al. (1998). With its 353 directed ties, a relationship between the network structure and state attributes is difficult to obtain by simply inspecting the ties: we investigate these relationships through statistical modeling via ERGMs.



(a) Alaska

(b) Florida

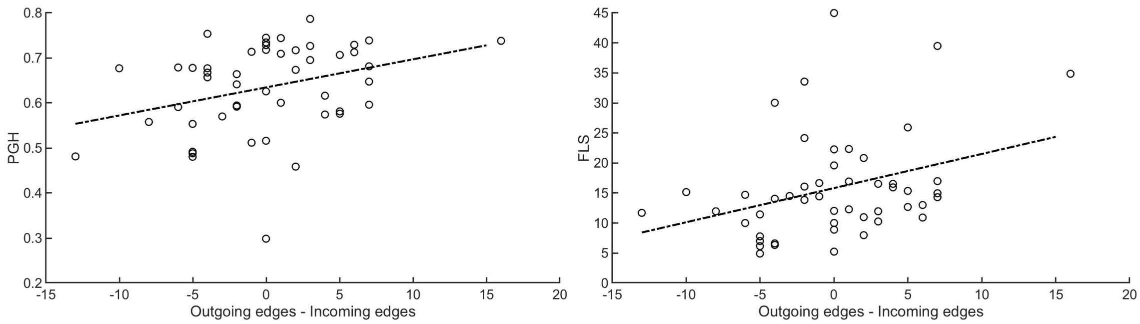
(c) Georgia

(d) Illinois

(e) Massachusetts

(f) Oregon

Figure 3: Six examples of interactions from the network of influence: Alaska (AK), Florida (FL), Georgia (GA), Illinois (IL), Massachusetts (MA), and Oregon (OR). Circles represent U.S. states and arrows causal influences.



(a) (b)

Figure 4: Scatter plots of (a) percent of gun homicide (PGH) vs. net out-degree in y^* and (b) firearm law strictness (FLS) vs net out-degree in y^*. Each black circle represents one U.S. state. The difference between outgoing edges and incoming edges is the net out-degree.

4.2 Predictors of causal relationships between states

We first build a baseline model (Model 1) using only the edges of the network. This is practically an Erdős–Rényi model whose ties independently occur with a fixed probability. Here, the term *edges* specifies the baseline of edge density for the fitted models. Next, following Section 3.2, we develop a set of ERGMs (Model 2-8), with a progressively increasing number of model statistics, and, ultimately, we build Model 9 with fewer, refined model statistics. Specifically, Model 2 is built upon Model 1 by incorporating network structural factors (mutuality, GWDSP, and GWESP), which is then used to create Models 3-8 by introducing percent of gun homicide, median household income, population, firearm law strictness, citizen ideology, and geographic neighborhood; results are presented in Table 4.

For a given model in Table 4, a model statistic listed with its $\vec{\theta}$ value is statistically significant as indicated by ***, **, and * with p less than 0.001, 0.01, and 0.05, respectively. Significance is established by comparison against the standard error in the MCMC MLE process (Hunter & Handcock, 2006). For example, with respect to Model 6 and *in-edges:FLS*, we have $\theta = -0.032 < 0$, indicating that a tie between two states is less likely to arise if the state being influenced ('in-edge') has higher 'firearm law strictness' ($p < 0.01$).

We next compare Model 1 vis-à-vis Models 2-8 with the AIC as the figure of merit; see Table 4 (bottom row). Smaller AIC values indicate improvement in model fitting. For Model 1, we have AIC = 1991 and with added covariates in Models 2-8, we find that AIC values drop, down to 1906 for Model 8. While in general one may expect AIC values to drop as more covariates are added to the models, inspecting Table 4 we also reveal that there are particular statistics that matter more than others. Hence, entries with a degree of statistical significance inform the development of Model 9 with reduced, yet relevant, model statistics. In this process, we excluded covariates associated with median household income (MHI) in Model 9 since this statistic does not consistently demonstrate significance, e.g., comparing Model 6-8 against Models 4-5.

Based on Model 3-4 in Table 4, the positive entry in $\vec{\theta}$ corresponding to *nodal effect of out-edges* for percent of gun homicide shows that, conditioned on the rest of network, a state with relatively higher (lower) percent of gun homicide is more (less) likely to influence the other states with respect to patterns of gun acquisition. A complementary result is the negative entry of *nodal effect of in-edges* for percent of gun homicide, which shows that a state with relatively higher (lower) percent of gun homicide is less (more) likely to be influenced by other states. An illustration of this case is provided in Fig. 4a, where we observe a positive correlation between a state's percent of gun homicide and the state's net out-degree in y^* (see also Table E.1 in Appendix 6.5). To avoid deviations caused by extreme values of nodal attributes from certain states, rank correlation between percent of gun homicide and net out-degree is measured using Kendall's τ coefficient ($\tau = 0.235$, $p < 0.05$) (Kendall, 1948). Given that net out-degree indicates that a state is in more of a leader role than in a follower role, the results indicate that states with higher percent of gun homicide are more likely to be leaders, consistent with the results obtained through ERGM. In this vein, Illinois and Georgia, which rank higher in terms of percent of gun homicide, show clear patterns of influencing other states than being influenced. On the contrary, states like Alaska and Oregon, which rank low in percent of gun homicide, are likely influenced by other states, as also seen in Fig. 3.

Following Models 6-8, the positive entry in $\vec{\theta}$ corresponding to *nodal effect of out-edges* for firearm law strictness indicates that the states with higher (lower) firearm law strictness have higher (lower) chance to influence other states. Moreover, the negative entry in $\vec{\theta}$ corresponding to *nodal effect of in-edges* for firearm law strictness indicates that the states with higher (lower) firearm law strictness have lower (higher) chance to be influenced by the other states. Similar to percent of gun homicide, a positive rank correlation is measured by Kendall's τ coefficient ($\tau = 0.242$, $p < 0.05$) between state firearm law strictness and net out-degree in y^* (see Fig. 4b), indicating that states with stricter firearm laws take more leadership roles than those with more permissive firearm laws, which is consistent with the results suggested of ERGM. The *edge covariate of abstract distance* for citizen ideology further shows that influence between two states exists with a higher chance if there is greater difference in the citizen ideology of those two states. Similarly, *no shared border* with a positive corresponding entry indicates that influence have higher chance to exist between two states without a shared border. However this statistic is not consistent between Models 8 and 9, and is not robust against edge density (see Appendix).

We also point out the possibility of correlation/interplay between some model statistics. For example, as we progressively add more model statistics, both *out-edges* and *in-edges* percent of gun homicide lose their significance in Models 6-8. Moreover, the corresponding θ value decreases in magnitude and at the same time standard error increases, indicating their variability is increased in Models 6-8. This is possibly because the newly added statistics in ERGM correlate with *out-edges* and *in-edges* percent of gun homicide. We therefore still opt to keep these two statistics in Model 9 with a reduced number of statistics. Another case is observed when transitioning from Model 5 to Model 6. *Nodal effect of out-edges* and *nodal effect of in-edges* for median household income becomes significant predictors in Model 6, possibly because of the correlation between this model statistic and the newly added terms related to firearm law strictness. Through this systematic study, we also reveal that covariates associated with geometrically weighted edgewise shared partners (GWDSP), median household income, and population do not inform our ERGMs with statistical significance. Likewise, median household income and population are not robust across different models, which is possibly due to correlations among model statistics.

Ultimately, based on Model 9, when all the other conditions are fixed: (i) states with higher (lower) level of *firearm-related crime prevalence* (related to percent of gun homicide) have relatively higher (lower) chance to influence the other states ($p < 0.05$); (ii) states with higher (lower) level of *firearm-related crime prevalence* (related to percent of gun homicide) have relatively lower (higher) chance to be influenced by other states ($p < 0.1$); (iii) the states with higher (lower) firearm law strictness have relatively higher (lower) chance to influenced the other states ($p < 0.05$); (iv) the states with higher (lower) firearm law strictness have relatively lower (higher) chance to be influenced ($p < 0.05$); (v) influences have higher (lower) chances to exist between two states which have larger (smaller) dissimilarity in their citizen ideology ($p < 0.05$); and (vi) influences have higher (lower) chances to exist between two states which have no shared geographical border ($p < 0.1$).

For *transitivity* (GWESP) and *mutuality*, the entries of $\vec{\theta}$ are statistically significant, with positive values across most of the models. That is, conditioned on the rest of the network, a tie has higher chance to form between two U.S. states if these two states have a common neighbor (transitivity as measured by GWESP, $p < 0.001$) and, to a lesser degree, if another tie in the opposite direction already exists between the same two states (mutuality, $p < 0.05$). One can also interpret the positive parameter for GWESP as an indication of the existence of edges with shared partners forming triangular structures in y^*. Indeed, one can find many examples demonstrating the existence of transitivity and mutuality. For example, we detect a transitive triad among North Dakota, Florida, Alaska, where North Dakota through Florida influences Alaska, and in addition it influences Alaska directly. With regards to mutuality, we reveal for example Illinois influences and is influenced by Arkansas, Colorado, Idaho, South Carolina, and Tennessee, among others.

Furthermore, Model 9 can help evaluate the odds that a tie exists between two states, following Appendix 6.3. For example, we find the existence of a tie from Indiana, Mississippi, and Missouri to Illinois corresponds respectively to a conditional probability of 0.22, 0.28, and 0.24, and from Arizona to New York with a conditional probability of 0.36 – higher than the average edge density of 0.15 in the network of influence y^*. Model 9 can also help reveal the importance of transitivity in view of Appendix 6.3, where for example we find the odds of a tie to exist from New York to Rhode Island is predicted to be 40 times higher when incorporating the transitivity term in the ERGM than not. To expand on this aspect, we perform a sensitivity test where we retain and remove from Model 9 separately mutuality, GWESP, or two PGH-related terms, and next compute how removal of a covariate affects the likelihood of predicting ties. This calculation for GWESP and PGH-related terms leads to a ranking of state-to-state influences, from the influence most affected by a covariate to the one least affected by that covariate. For mutuality, this calculation statistically yields indistinguishable effects, so that no ranking is provided, but only a sample of 10 state-to-state influences, see Table 1, Table 2, and Table 3. It is critical to note that Model 9 is derived based on random sampling of graphs, and hence, as expected, not all the ties tested exist in the single sample y^*. This information is provided in the third column of each table.

Sender state	Receiver state	Does a tie exist in y^*
Alabama	Illinois	N
Arizona	Florida	N
Arkansas	Illinois	Y
Colorado	Illinois	Y
Florida	North Dakota	N
Idaho	West Virginia	N
Illinois	Arkansas	Y
Illinois	Oklahoma	Y
Illinois	Tennessee	Y
Nevada	Washington	N

Table 1: 10 randomly picked ties in the network of influence, strongly influenced by *mutuality*.

Rank	Sender state	Receiver state	Does a tie exist in y^*
1	Colorado	Illinois	Y
2	New York	Rhode Island	Y
3	Ohio	Rhode Island	N
4	Arizona	Washington	N
5	Maine	Rhode Island	N
6	Rhode Island	Illinois	Y
7	North Dakota	Delaware	Y
8	Georgia	Rhode Island	Y
9	Mississippi	Idaho	N
10	Maine	Illinois	N

Table 2: Top 10 ties in the network of influence, most influenced by *GWESP*.

Rank	Sender state	Receiver state	Does a tie exist in y^*
1	Illinois	South Dakota	N
2	California	South Dakota	N
3	Louisiana	Maine	N
4	Alabama	New Hampshire	N
5	Illinois	North Dakota	Y
6	Illinois	Wyoming	N
7	Missouri	Vermont	N
8	Illinois	Vermont	N
9	Missouri	Montana	Y
10	Illinois	Montana	Y

Table 3: Top 10 ties in the network of influence, most influenced by PGH.

Table 4: Estimated parameter entries of $\vec{\theta}$ for fitted models and their corresponding standard errors (in parenthesis) are listed on the table; p values are denoted by *** for < 0.001, ** for < 0.01, and * for < 0.05, respectively; see Section 6.2.1 for definitions of model terms.

Model statistic	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**	**Model 7**	**Model 8**	**Model 9**
edges	-1.734(0.058)***	-2.772(0.249)***	-2.781(0.593)***	-3.056(0.777)***	-3.404(0.809)***	-3.461(0.785)***	-3.973(0.861)***	-4.269(0.842)***	-3.886(0.487)***
mutuality		0.463(0.212)*	0.495(0.205)*	0.499(0.207)*	0.486(0.207)*	0.562(0.221)*	0.546(0.213)*	0.545(0.211)**	0.495(0.212)*
gwdsp		-0.043(0.029)	-0.019(0.031)	-0.017(0.032)	-0.019(0.032)	0.026(0.034)	-0.015(0.032)	0.018(0.033)	—
gwesp		0.663(0.085)***	0.657(0.087)***	0.648(0.086)***	0.643(0.086)***	0.622(0.090)***	0.598(0.089)***	0.592(0.089)***	0.630(0.086)***
out-edges : PGH			1.301(0.592)*	1.304(0.580)*	1.619(0.663)*	1.208(0.725)	1.346(0.738)	1.294(0.727)	1.398(0.596)*
in-edges : PGH			-1.479(0.626)*	-1.372(0.638)*	-1.035(0.700)	-0.748(0.738)	-0.495(0.751)	-0.571(0.721)	-0.915(0.544)
edge covariate : PGH			-0.202(0.347)	-0.175(0.357)	-0.305(0.378)	-0.297(0.378)	-0.247(0.410)	-0.347(0.403)	—
out-edges : MHI				-0.022(0.054)	-0.013(0.054)	-0.193(0.079)*	-0.186(0.076)*	-0.187(0.079)*	—
in-edges : MHI				0.071(0.057)	0.080(0.057)	0.221(0.078)**	0.210(0.076)**	0.210(0.076)**	—
edge covariate : MHI				-0.369(0.248)	-0.444(0.257)	-0.444(0.258)	-0.438(0.263)	-0.485(0.273)	—
out-edges : PPL					-0.017(0.013)	-0.038(0.015)**	-0.028(0.015)	-0.028(0.015)	—
in-edges : PPL					-0.019(0.013)	-0.001(0.014)	0.008(0.014)	0.008(0.015)	—
edge covariate : PPL					0.677(0.487)	0.641(0.482)	0.456(0.515)	0.432(0.504)	—
out-edges : FLS						0.037(0.011)***	0.034(0.012)**	0.035(0.012)**	0.012(0.006)*
in-edges : FLS						-0.032(0.011)**	-0.036(0.011)**	-0.035(0.011)**	-0.013(0.007)*
edge covariate : FLS						0.009(0.319)	0.212(0.349)	0.214(0.355)	—
out-edges : CTI							0.001(0.005)	0.001(0.005)	—
in-edges : CTI							0.006(0.004)	0.005(0.004)	—
edge covariate : CTI							0.597(0.270)*	0.552(0.262)*	0.575(0.238)*
no shared border								0.471(0.239)*	0.425(0.230)
AIC	1991	1923	1918	1921	1924	1911	1909	1906	1905

[1] As for estimated parameters, covariate *edges* corresponds to the baseline of edge density for the fitted models; *mutuality* relates to the tendency of forming reciprocal ties; *gwesp* and *gwdsp* separately capture characteristics of transitivity in the network; *out-edges* and *in-edges* measure the association that one nodal attribute has with the node at the origin of a tie and that at the end of a tie; and *edge covariate* measures how other pairwise relations (similarity/dissimilarity in one nodal attribute) between two nodes affect tie formation. As for the abbreviations of nodal attributes included, PGH is the gun homicide as a percent of all homicides in a state; MHI stands for inflation-free median household income; PPL is state population size; FLS is firearm law strictness as the count number of restrictive firearm-related laws in one state; and CTI is citizen ideology.

4.3 Assessment of the optimal model (goodness-of-fit)

Model 9 brings together the most relevant covariates in our modeling effort. In order to assess whether it provides reliable statistical predictions, we perform a simulation study. In particular, we generate a sample of $2,000$ random networks, and, guided by the literature (Hunter, Goodreau, et al., 2008), we obtain the distributions of covariates out-degree, in-degree, geodesic distance, and dyadwise shared partner over these simulated networks. We compute the distributions of the same covariates for the inferred network of influence y^*, see Fig. 5. Therein, we report box plots for the distribution of each of the four covariates as found in the $2,000$ random network samples along with black markers and lines as found in the inferred network y^*. The four covariates corresponding to y^* in most cases match with the median (blue diamonds) in the box plots. As for dyadwise shared partner and geodesic distance, the match is almost perfect, while for out/in-degree distributions, simulated networks could only reflect the general trends in y^*, indicating that there exists, in the inferred network data, a certain degree of complexity, which could not be captured by the selected covariates in Model 9. Overall, we conclude that Model 9 is a good mathematical representation, capturing the formative reasons that explain the network of influence y^*.

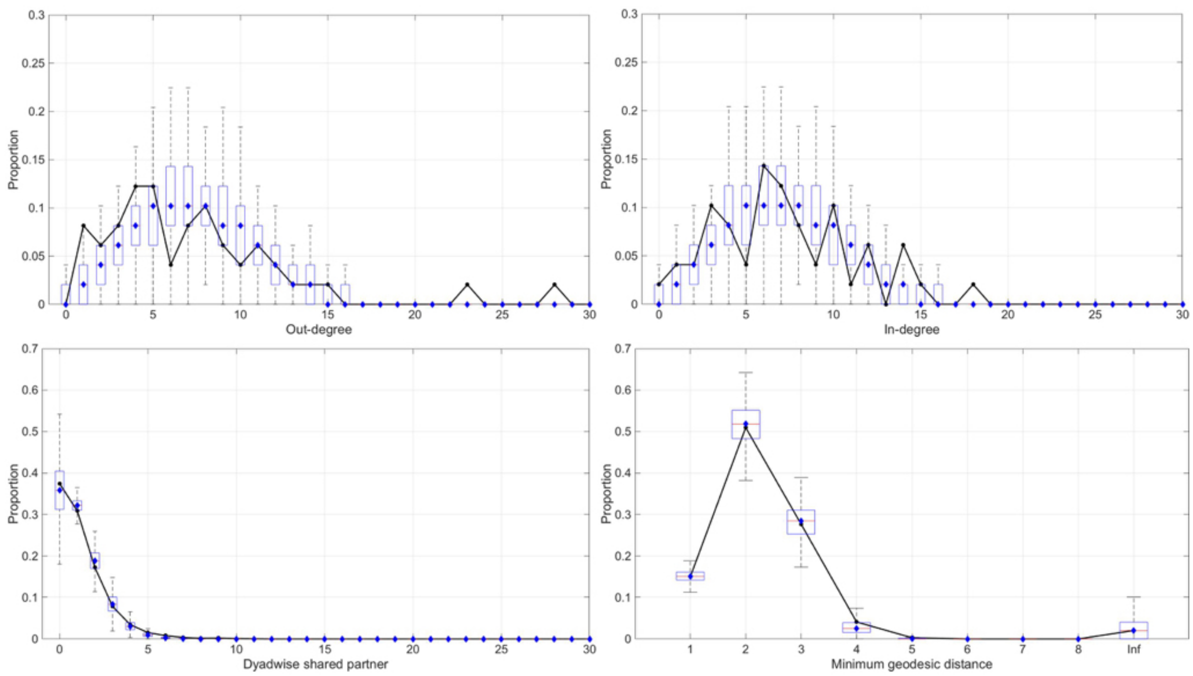


Figure 5: Distributions of covariates out-degree, in-degree, dyadwise shared partner, and geodesic distance in inferred network of influence y^* (black curves) and in $2,000$ randomly simulated networks based on Model 9 (box plots).

5 DISCUSSION AND CONCLUSIONS

With firearm-related crimes and self-inflicted harms severely impacting the quality of life of Americans, it is imperative that we seek to deeply understand the reasons behind firearm acquisition in the United States. With this overall goal in mind, here we put forth a mathematical framework to investigate whether or not U.S. states influence each other in their firearm acquisition patterns, and, if they do, what are the formative factors that potentially explain such influences. Our study reveals the underlying network of influence of U.S. states informing which states are more influential on others, and develops statistical models that uncover how crime rates, citizen ideology, income levels, population, and the legal environment could explain these influences.

There is growing evidence that U.S. states interact with one another in various ways. With respect to firearms, Andrade et al. (2020) determine that firearm laws, geographic proximity, and population shape the way in which firearms are transferred across state borders. Likewise, Porfiri et al. (2020) offer evidence in favor of an influence between states that are geographically close with respect to firearm acquisition, whether they are restrictive or permissive in their firearm-related legal environment. Insights into the network of influence with respect to firearm-related policies are established by Grabow et al. (2016), pointing at the possibility of policy diffusion across states. Through the application of transfer entropy, we further detail state-to-state interactions with respect to firearm acquisition. Interactions are in general non-symmetric, where states may influence other states, while not being influenced by them. Our results indicate that some states may act as 'hubs', such as the state of Illinois, with a large number of outgoing and/or incoming ties, while others, such as the state of Alaska, may have a large degree of isolation, with only a few ties with other states.

Through exponential-family random graph models (ERGMs), we explain next the reasons why states influence each other based on state-level attributes and network structural factors. We reveal that *percent of gun homicide*, *firearm law strictness* and *citizen ideology* as state-level attributes help explain this influence. With respect to percent of gun homicide, a state with more firearm homicides is more likely to influence other states and less likely be influenced by other states. These findings resonate with previously published work (Wallace, 2015) and survey results (Gallup Corporation, n.d.), where it is reported that safety plays an important role among citizens when deciding to acquire a firearm. From safety to collective behavior in firearm acquisition, perception of public safety can play an important role. Researchers estimate/predict citizens' perception of safety via surveys at the individual level (Austin & Furr, 2002), by analysis of street view images in cities using deep-learning models (Zhang et al., 2021), and through natural language processing and emotion analysis on Twitter messages at population level (Dyer & Kolic, 2020; Gourévitch & Eggermont, 2007). Proper measures at state level, such as quantifying public sentiment regarding "belief in a dangerous world" through the analysis of geographically-tagged social media messages has the potential to provide promising future extensions over current modeling efforts.

With regards to our finding that states with higher percent of gun homicide (PGH) are in leadership roles, it is plausible that citizens in states with higher PGH may have a stronger need of self protection and can therefore be more reactive in acquiring firearms. Such effects could diffuse to states with lower PGH, which would exhibit a follower-type behavior. Furthermore, under the theory that firearm ownership correlates positively with the prevalence of gun crimes (Siegel et al., 2013), higher firearm prevalence in states with higher PGH and combined with permissive gun laws become potential sources to affect firearm markets in other states, e.g., through firearm trafficking (Andrade et al., 2020; Kleck, 1999), exemplifying a leader-follower relationship between the states. With respect to firearm law strictness, we reveal that a state with stricter firearm laws is more likely to influence others and less likely be influenced by other states. One may suggest that this indicates that such laws may dampen firearm acquisition, thereby reducing the likelihood that a state can be influenced by another state's firearm acquisition activities. Given that the more common firearm laws contain restrictions on when, how, and who may purchase new guns, it is plausible that the presence of such laws creates a legal framework that insulates the state's citizens somewhat from outside influences. Results further indicate that background checks in states with different citizen ideology can influence each other; however, given the one-month time resolution of the data, we can claim only that such influences arise with a one month of delay time. This delay time also helps support the results explaining influences are more likely between states that do not share a border, that is, some finite time is needed for such influences to propagate over relatively larger distances.

In view of the above discussions, our study offers a few insights with respect to policy making. Results indicate that the percent of homicides committed with guns is a critical parameter in the formation of ties between states. This may be due to common factors that drive overall crime rates (such as poverty and unemployment), affinity among citizens in terms of the way they react to crime in their neighborhoods, or other factors. Clearly, programs and policies that help to reduce gun violence (whether homicides, suicides, or injuries) will not only promote the health of Americans and reduce healthcare costs (Callcut et al., 2018; Degli Esposti et al., 2023), but may also have the unintended effect of reducing state-to-state influences that may otherwise drive the ever-increasing rates of firearm acquisition in the U.S.

From the viewpoint of network structural factors, we reveal that *transitivity* and *mutuality* are also linked to state-to-state influences – characteristics that may have been overlooked in previous work. These two factors are associated with the particular ways states are connected to each other through ties. Transitivity is related to the well-known concept of ‘a friend of my friend is my friend’, while mutuality refers to the presence of reciprocated ties between a pair of states. We find that ties signifying an influence about firearm acquisition are more likely to form if they promote transitivity and mutuality. To a certain degree, tie formations are pervasive as new ties will promote newer ties, and hence strengthen state-to-state influences. Furthermore, ERGMs consistently suggest a negative relationship in edge density, indicating that the network tends to be more sparse than not. This therefore indicates a mechanism that modulates the number of ties in the network. Combined with transitivity, this potentially suggests a network with clusters of states.

With the implementation of ERGMs, this study reveals a refined model, Model 9, containing only the most relevant parameters. Model 9 can also be utilized to perform predictions. For example, it predicts in Section 4.2 higher odds for ties to exist from Indiana, Mississippi, and Missouri to Illinois, which can perhaps be expected, as the results resonate with (Andrade et al., 2020) where these ties were revealed as pathways of illegal firearm trafficking. Another result is the existence of a tie from Arizona to New York with higher odds, which is possibly unexpected since these states are geographically distanced and their political landscapes are different.

The results in this study should be considered under several limitations. While inferences rooted in transfer entropy have proven to shed light in a broad range of disciplines, we acknowledge the absence of a ground truth to back our claims. Furthermore, this study is limited to five candidate formative factors, although other factors associated with, for example, hunting activities could also be related to firearm acquisition. In the modeling process, this study does not consider temporal changes in covariates, such as fluctuations in the economy and time instants at which firearm policies are enacted, and the covariates supporting the ERGMs are time averaged over the study time range. Due to the time resolution and length of data, it was not possible to capture the dynamics at a higher temporal resolution, nor was it possible to condition transfer entropy computations and/or increase the number of bins in the data (Paninski, 2003). Were more detailed data available, it would be possible to unveil additional information about the firearm acquisition landscape in the U.S. For example, it would be possible to study how citizen ideology plays a role on state-to-state influences at shorter time scales, i.e., between neighboring states. Since it was not possible to condition transfer entropy values on the activity of the remaining states, the resulting pairwise state-to-state interactions may also indicate indirect influence from cascade effects, or the existence of a common driver. A cascade effect arises between two nodes due to some influence transmitting from one to the other through a common neighbor. It is therefore likely that some of the influences revealed in this study may be redundant or overestimate the presence of some ties, such as in the way described by GWESP (transitivity). To deal with the outcome of redundant ties due a common driver, model statistics related to degree distribution could be added in future modeling attempts. Further, we note that Andrade et al. (2020) find that states with stricter firearm laws may be subject to increased illegal firearm trafficking from states with looser regulations. Because the movement of illegal guns is not tracked through federal background checks, this possibility is an important limitation of the results presented here.

Overall, a systems-level approach should be used to better understand the underlying factors for policy adoption among states, the dynamic nature of state influences, and the ways in which these factors affect firearm-related harms. Unfortunately, authors have identified the lack of high-quality data on legal and illegal firearms, firearm-related harms including injuries, public opinion on firearms and their appropriate use, systems to track the effectiveness of laws intended to remove guns from those deemed to be a danger, for all states over time as major limitations to conducting this necessary evidence-based research (Callcut et al., 2018; Nagin et al., 2020).

To conclude, this study provides a data-driven, mathematical and computational framework by integrating transfer entropy with ERGMs. The results expand our understanding of which states influence each other in terms of firearm acquisition and explain the reasons of such influences with respect to crime rates, citizen ideology, income levels, population, and the legal environment. The presented mathematical framework will inform data-driven modeling efforts at the intersection of complex systems and network dynamics, and the results have the potential to impact research in public health, criminology, and policy making.

6 APPENDIX

6.1 Appendix A: Sub-steps for inference of the network of influence

6.1.1 Computation of Transfer Entropy

The monthly BC time series of each state is decomposed into trend-cycle, seasonal, and irregular components, using TRAMO/SEATS of *EViews* (Hood et al., 2000). The seasonal and trend-cycle components are removed from the original time series to generate detrended, seasonally adjusted BC series, see, e.g., (Porfiri et al., 2019). These processed series are denoted as $B_i(t)$, where $i \in \mathcal{S}$ is the state index; $\mathcal{S}$ is the set of $n = 49$ states examined in this work and t from $1, ..., 228$ is the time index. For each $B_i(t)$, the augmented Dickey-Fuller test is performed to ensure stationarity at a significance level of 0.05.

Time series are next converted to symbols. Symbolization is a common practice to capture the underlying behavior of dynamical systems, especially in the case of limited data (Staniek & Lehnertz, 2008). Numerical values in $B_i(t)$ are converted to three symbols ('0', '1', and '2'), which is the maximum number of symbols admissible in our study, as determined by the bias-variance balance criterion (Paninski, 2003). Each $B_i(t)$ is divided into three equal percentiles, where a specific value in $B_i(t)$ is symbolized as '0', '1', or '2' if the value falls either in the $1 - 32^{\text{th}}$, $33 - 65^{\text{th}}$, or $66 - 100^{\text{th}}$ percentile, respectively. The symbolized BC series are denoted by $B_i^S(t)$.

Given the time series $B_i^S(t)$ and $B_j^S(t)$ for two different states $i, j \in \mathcal{S}$, we have that $B_i^S(t)$ influences $B_j^S(t)$, if knowledge of $B_i^S(t)$ at time t improves the prediction of $B_j^S(t)$ from time t to $t+1$. This influence can be quantified by computing transfer entropy from $B_i^S(t)$ and $B_j^S(t)$. We use the notation $TE^{B_i^S \mapsto B_j^S}$ to denote this calculation. Computation of transfer entropy is very well established in the literature (Bossomaier et al., 2016).

6.1.2 Identification of the network of influence

TE values are computed between all the pairs of states, except Hawaii, using their symbolized BC time series. TE informs the existence and intensity of directed ties between the states. In such a setting, we have a network y^o with U.S. states as nodes and whose ties between the nodes are weighted by TE values. We denote with $a_{i,j}^o$ the weight of a directed tie from node i to j in y^o, that is,

$$a_{i,j}^o = \begin{cases} TE^{B_i^S \mapsto B_j^S} & \text{if } i \neq j \ , \\ 0 & \text{if } i = j. \end{cases} \tag{A.1}$$

Network y^o has $n(n-1)$ ties, but only the ties with weights that are substantially large are of interest, since small TE values are not reliable indicators of influence. To this end, ties with relatively large weights are kept and all the others are removed from y^o. The figure of merit in this process was to achieve an edge density of 15%, that is, we remove $n(n-1) \times 85\%$ of the ties from the network (see Section 6.4 for a robustness analysis with respect to a range of different thresholds). This is done by setting a threshold e at the 85^{th} percentile of the distribution of all $n(n-1)$ TE values calculated. We generate a new, unweighted directed network y^* called the network of influence, defined by the adjacency matrix

$$a_{i,j} = \begin{cases} 1 & \text{if } a_{i,j}^o > e \ , \\ 0 & \text{otherwise.} \end{cases} \tag{A.2}$$

To put into context, y^* describes a network of ties, where each tie signifies a relatively strong causal influence between a pair of U.S. states in terms of temporal firearm acquisition patterning. While y^* is the representation of ties underlying state-to-state influences, this does not shed light on the formative reasons behind why these ties form.

6.2 Appendix B: Sub-steps for identification of the formative reasons of the network of influence

6.2.1 Model statistics in ERGM

We next describe the model statistics considered. Here, model statistics refer to specific formulae used to measure/quantify (i) a particular attribute for each state based on its incoming/outgoing ties, (ii) how any two states sharing a tie compare in terms of their attributes, and (iii) network structural factors. The model statistics in this manuscript are based on the state-level attributes in Table B.1 with their measures described in Section 2:

State-level (nodal) attributes	VIF($\overline{\mathcal{A}}$)
Gun homicide as a percent of all homicides (PGH)	1.42
Inflation-adjusted median household income (MHI)	1.52
State population size (PPL)	1.67
Firearm law strictness as the count number of restrictive firearm-related laws (FLS)	2.61
Citizen ideology (CTI)	1.48

Table B.1: Informed by Andrade et al. (2020), Boine et al. (2020), Cook et al. (2011), Kelley and Ellison (2021), Liu and Wiebe (2019), and Porfiri et al. (2019), we consider five attributes to explore formation of causal influences with respect to firearm acquisition.

As we treat each state as a node, the above described attributes are also known as 'nodal' attributes. Two of them, median house hold income and population, have wide ranges, so that they are expressed in the units of \$10,000 and 1,000,000 people, respectively. Let $\mathcal{A}_i(t)$ denote the time series of a nodal attribute $\mathcal{A}$ of state i, where $\mathcal{A} \in \{\text{PGH, MHI, PPL, FLS, CTI}\}$. Over the available time span, we compute average values $\overline{\mathcal{A}}_i$ of $\mathcal{A}_i(t)$ and calculate the abstract distance between two states,

$$D(i,j) = \frac{\sum_t |\mathcal{A}_i(t) - \mathcal{A}_j(t)|}{M_D} \in [0,1], \tag{B.1}$$

with normalizing factor M_D as the maximum value of $\sum_t |\mathcal{A}_i(t) - \mathcal{A}_j(t)|$ over all different pairs $(i,\ j)$. For ERGM, $D(i,j)$ and $\overline{\mathcal{A}}_i$ are known respectively as dyadic covariates and nodal covariates (see Appendix 6.5 for the ranking of states in these nodal measurements). To check their collinearity, variance inflation factor (VIF) of the considered nodal covariates is computed, see Table B.1 (Belsley et al., 2005). These values are all less than five indicating that there is no strong collinearity between them. For this reason, we continue with utilizing all the covariates in ERGM.

Using $\overline{\mathcal{A}}_i$ and $D(i,j)$, we formulate the following covariates: nodal effect of out-edges, nodal effect of in-edges, and edge covariate of abstract distance (Harris, 2013; Morris et al., 2008), see Table B.2 (top three rows). The nodal effects of out-edges and in-edges measure the association that attribute $\mathcal{A}$ has with the node at the origin of a tie and that at the end of a tie. In addition to considering node-to-node interactions, we also investigate two commonly observed structural features in social networks: mutuality and transitivity. As shown in Fig. 6, mutuality captures the tendency to form more reciprocal ties in a directed network (see also Table B.2 for model statistics) and transitivity the tendency of a tie to form if it completes a triangular subgraph. To discern whether there exists a certain degree of transitivity in y^*, we utilize the geometrically weighted edgewise shared partners (GWESP). A similar metric is the geometrically weighted dyadwise shared partners (GWDSP), where a dyad refers to a pair of nodes (connected or not). Both GWESP and GWDSP adjust the weights on counts of subgraphs depending on the number of shared neighbors; see Table B.2 for model statistics and the graphs in Fig. 6 illustrating examples of one, two, and three shared neighbors. Finally, considering influences from geographical factors, we introduce a model statistic to measure the tendency of tie formation between two states that share a border, see Table B.2 (bottom row). Inspecting Table B.2, it is critical to note that model statistics depend on static measures, such as $\overline{\mathcal{A}}_i$, $D(i,j)$, and the characteristics of the network. This is consistent with the mathematical construct of ERGM and for this reason, this part of the study does not focus on causal inferences, but rather on understanding how these statistics can inform the formation of a tie.

Model statistics	Formula used in the corresponding entry of $\vec{Z}(y)$
Nodal effect of out-edges for nodal attribute X	$\sum_{(i,j)\in E} \overline{\mathcal{A}}_i y_{ij}$
Nodal effect of in-edges for nodal attribute X	$\sum_{(i,j)\in E} \overline{\mathcal{A}}_j y_{ij}$
Edge covariate of abstract distance for nodal attribute X	$\sum_{(i,j)} D(i,j) y_{ij}$
Mutuality	$\sum_{(i<j)} y_{ij} y_{ji}$
GWESP	$e^{\alpha} \sum_{q=1}^{n-2} [1-(1-e^{-\alpha})^q] \; ESP_q(y)$, $\alpha = 0.5$
GWDSP	$e^{\alpha} \sum_{q=1}^{n-2} [1-(1-e^{-\alpha})^q] \; DSP_q(y)$, $\alpha = 0.5$
Geographical factor: (no) shared border	$\sum_{(i,j)\in G} y_{ij}, \; G = \{(i,j) \vert \text{state } i \text{ and state } j \text{ have (no) shared border}\}$

Table B.2: Mathematical definitions of specific model statistic for the ERGMs. E denotes the set of edges; for covariates related to nodal attributes, we set $\mathcal{A} \in$ {PGH, MHI, PPL, FLS, and CTI} based on Table B.1; $ESP_q(y)$ is the number of edges between two nodes that have q shared neighbors; and $DSP_q(y)$ is the number of dyads between two nodes that have q shared neighbors; see (Harris, 2013; Morris et al., 2008), for details.

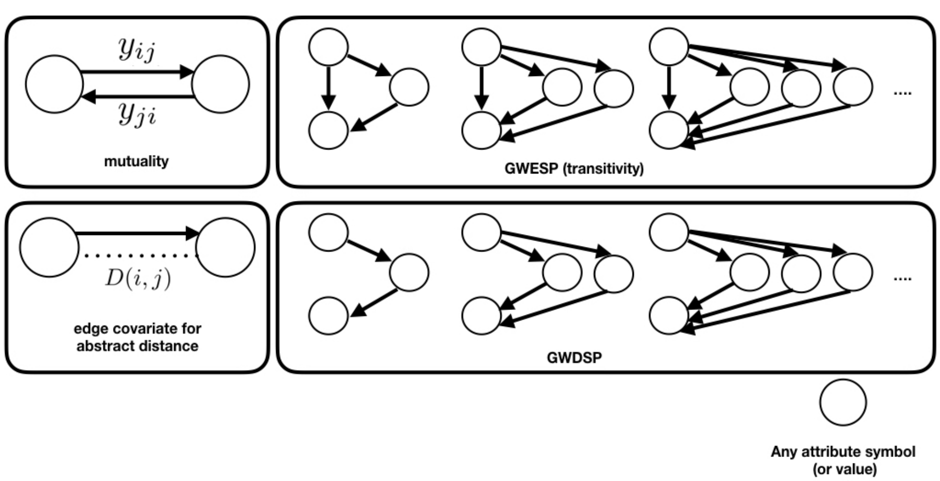


Figure 6: Illustration of network structural factors.

To reveal the key formative reasons for the network of influence, multiple models with different combinations of model statistics are fitted in the framework of ERGM; see Section 4.2 for results obtained from a set of nested ERGMs.

6.2.2 Model assessment: ERGM goodness-of-fit

The maximum likelihood estimation is the basis of model fitting, but this does not guarantee that the random networks generated by ERGM will perfectly resemble y^*. A goodness-of-fit procedure should be performed (Hunter, Goodreau, et al., 2008; Hunter, Handcock, et al., 2008). Given an ERGM with certain specifications and estimated parameters, this procedure comprises of two steps: (i) simulation by Markov Chain Monte Carlo sampling scheme (Hunter & Handcock, 2006) to generate a sample of random networks by the given ERGM with estimated parameters; and (ii) comparison of a set of metrics from y^* to the distribution for the same set of metrics obtained from the simulated networks in (i). In this manuscript, the selected metrics are *in-degree distribution, out-degree distribution, dyadwise shared partner distribution*, and *geodesic distance distribution* (Hunter, Goodreau, et al., 2008). The distribution of these metrics for simulated networks and y^* are presented in Section 4.3.

6.3 Appendix C: Interpretation of parameters and prediction of ties in ERGMs

The interpretation of $\vec{\theta}$ is as follows. Consider two networks: y_1, where one specific tie exists ($y_{ij} = 1$) and y_2, where the same tie is removed ($y_{ij} = 0$), without altering the remaining ties y^c. We compare the likelihood of the existence or absence of this tie, using

$$\log\left(\frac{P(\ y_{ij} = 1 \mid \vec{\theta},\ y^c\ )}{P(\ y_{ij} = 0 \mid \vec{\theta},\ y^c\ )}\right), \tag{C.1}$$

which, based on equations (1) and (2), can further be simplified as (Harris, 2013)

$$\vec{\theta}^{\,T}(\vec{Z}(y_1) - \vec{Z}(y_2)). \tag{C.2}$$

Let us consider the example of ‘the number of triangles’ in the network as the sole model statistic. Given that adding the tie y_{ij} would increase the number of triangles, $\vec{Z}(y_1) - \vec{Z}(y_2)$ will be positive. If the corresponding entry in $\vec{\theta}$ is positive (negative), then (C.2) will be positive (negative), implying that the tie y_{ij} is more (less) likely to exist than being absent when it comes to promoting an increase in the count of triangles.

Furthermore, with estimated parameters $\vec{\theta}_9$ in Model 9, the conditional probability that a tie exists $P(\ y_{ij} = 1 \mid \vec{\theta}_9,\ y^c\ )$ or is absent $P(\ y_{ij} = 0 \mid \vec{\theta}_9,\ y^c\ )$ in the network of influence can be predicted through Eq. (C.1) and (C.2). Here, probability is conditioned on fixing the rest of the network y^c consistent with ERGM. Also, we can perform a sensitivity analysis to study the effects of model parameters on the existence of ties. To this end, let (C.1) be defined for Model 9 as $T_{ij} = \log(P(\ y_{ij} = 1 \mid \vec{\theta}_9,\ y^c\ )/P(\ y_{ij} = 0 \mid \vec{\theta}_9,\ y^c\ ))$ as log-odds of tie existence. Define next $\vec{\theta}_9^{GWESP}$ as the vector obtained by removing GWESP from $\vec{\theta}_9$. Then, one can calculate the log-odds in the absence of the GWESP parameter as $T_{ij}^{GWESP} = log(P(\ y_{ij} = 1 \mid \vec{\theta}_9^{GWESP},\ y^c\ )/P(\ y_{ij} = 0 \mid \vec{\theta}_9^{GWESP},\ y^c\ ))$. Pair-wise comparison of T_{ij}^{GWESP} and T_{ij} then provides intuition as to how GWESP influences the prediction of ties between two states, relative to the other factors in the model. Similar analysis can then be conducted separately by isolating the mutuality term in the model $T_{ij}^{mutuality}$, or the two terms associated with percent of gun homicide (PGH), T_{ij}^{PGH}. Once again comparison between $T_{ij}^{mutuality}$ and T_{ij}, as well as between T_{ij}^{PGH} and T_{ij} will reveal the relative contribution of mutuality and PGH on tie formation. To focus on the most relevant effects, we retain only the ties whose conditional probability increases at least 0.1 units in this comparison procedure. Next, we rank these changes in probability from the largest to the smallest, and report the top 50 entries, see Table C.1, Table C.2, and Table C.3. Rank of ties corresponding to mutuality (Table C.1) is however selected by alphabetical order of states because mutuality term results in a fixed value of increase in odds of ties predicted. In Table 1 in Section 4.2, ties presented are picked randomly from the 50 ties in Table C.1.

6.4 Appendix D: Robustness of model parameters with varied edge-density levels

As pointed out in Section 6.1.2 *Identification of the network of influence*, edge density of the influence network under study is controlled by a threshold e on the transfer entropy (TE) values. If e is reduced, this will allow smaller TE values between two states to inform the presence of a tie. Since the formation of the network is an input to our statistical modeling effort, it is of interest to investigate how e could potentially alter the outcomes of this modeling. To this end, Model 9 obtained in Table 4 is next fitted under different edge densities, recalling that 15% is the baseline edge density used in the manuscript. The fit results are provided in Table D.1 and D.2, where the edge density is varied from 10% to 20%. This robustness study reveals that model statistics including *transitivity* (GWESP), *mutuality*, *nodal effect of out-edges* for percent of gun homicide, *nodal effect of out-edges* for firearm law strictness, and *edge covariate of abstract distance* for citizen ideology still maintain their respective statistical significance levels, except in a few cases that the corresponding p-values get perturbed to be slightly over 0.05. On the other hand, *nodal effect of in-edges* for firearm law strictness loses its significance in networks with edge densities less than or equal to 13%; *nodal effect of in-edges* for percent of gun homicide loses its significance when edge density of inferred network ranges between 11% and 15%. These two covariates however still remain significant predictors for larger edge densities. As for the term of *no shared border*, its parameter is not strictly significant for most of the inferred networks. Overall the results provide additional confidence in the validity of Model 9 and the key factors, mutuality, transitivity, percent of gun homicide, firearm law strictness, and citizen ideology that explain state-to-state influences.

Rank	Sender state	Receiver state	Does a tie exist in y^*
-	Alabama	Connecticut	N
-	Alabama	Illinois	N
-	Alabama	Pennsylvania	N
-	Alabama	Rhode Island	Y
-	Alabama	Utah	Y
-	Arizona	Florida	N
-	Arizona	Illinois	N
-	Arizona	Maine	N
-	Arizona	Minnesota	N
-	Arizona	New York	N
-	Arizona	Rhode Island	N
-	Arizona	South Carolina	N
-	Arizona	Vermont	N
-	Arkansas	Illinois	Y
-	California	Idaho	N
-	California	Oklahoma	N
-	Colorado	Delaware	N
-	Colorado	Illinois	Y
-	Colorado	Rhode Island	N
-	Colorado	South Carolina	N
-	Connecticut	Utah	N
-	Delaware	Alabama	N
-	Delaware	North Dakota	N
-	Florida	North Dakota	N
-	Idaho	Rhode Island	Y
-	Idaho	West Virginia	N
-	Illinois	Arkansas	Y
-	Illinois	Colorado	Y
-	Illinois	Idaho	Y
-	Illinois	Kansas	N
-	Illinois	New Jersey	N
-	Illinois	Oklahoma	Y
-	Illinois	Rhode Island	Y
-	Illinois	South Carolina	Y
-	Illinois	Tennessee	Y
-	Illinois	Wyoming	N
-	Kansas	Wisconsin	N
-	Kentucky	North Dakota	N
-	Kentucky	Rhode Island	N
-	Maine	Illinois	N
-	Mississippi	Maryland	N
-	Mississippi	Rhode Island	Y
-	Montana	Missouri	N
-	Montana	Washington	N
-	Nevada	Maine	N
-	Nevada	Rhode Island	Y
-	Nevada	Washington	N
-	New Jersey	Wyoming	N
-	New York	Rhode Island	Y
-	Ohio	Vermont	N

Table C.1: Potential ties of state-to-state influence ranked by $T_{ij} - T_{ij}^{mutuality}$.

Rank	Sender state	Receiver state	Does a tie exist in y^*
1	Colorado	Illinois	Y
2	New York	Rhode Island	Y
3	Ohio	Rhode Island	N
4	Arizona	Washington	N
5	Maine	Rhode Island	N
6	Rhode Island	Illinois	Y
7	North Dakota	Delaware	Y
8	Georgia	Rhode Island	Y
9	Mississippi	Idaho	N
10	Maine	Illinois	N
11	Rhode Island	Maine	N
12	Pennsylvania	Rhode Island	N
13	Utah	Missouri	N
14	Rhode Island	Connecticut	N
15	Illinois	Rhode Island	Y
16	Ohio	Maine	N
17	Louisiana	Illinois	N
18	Georgia	Illinois	N
19	Ohio	Colorado	N
20	Rhode Island	South Dakota	N
21	Delaware	Colorado	Y
22	Rhode Island	Kansas	N
23	Delaware	Rhode Island	N
24	Vermont	Oklahoma	N
25	Wisconsin	Florida	N
26	Illinois	Wyoming	N
27	Illinois	Iowa	N
28	Utah	Illinois	N
29	Delaware	North Dakota	N
30	Wisconsin	Illinois	N
31	Kentucky	Oklahoma	N
32	Rhode Island	Pennsylvania	N
33	Ohio	Vermont	N
34	Vermont	Illinois	N
35	Oregon	North Dakota	N
36	Vermont	Missouri	N
37	Oklahoma	Kentucky	N
38	Idaho	Mississippi	N
39	Arizona	South Carolina	N
40	Maine	Vermont	Y
41	Colorado	Vermont	Y
42	Colorado	Delaware	N
43	Rhode Island	Alabama	Y
44	Virginia	Colorado	N
45	Pennsylvania	Minnesota	Y
46	Rhode Island	Ohio	Y
47	Texas	Connecticut	N
48	Tennessee	Illinois	Y
49	Florida	Mississippi	N
50	Rhode Island	Colorado	Y

Table C.2: Potential ties of state-to-state influence ranked by $T_{ij} - T_{ij}^{GWESP}$.

Rank	Sender state	Receiver state	Does a tie exist in y^*
1	Illinois	South Dakota	N
2	California	South Dakota	N
3	Louisiana	Maine	N
4	Alabama	New Hampshire	N
5	Illinois	North Dakota	Y
6	Illinois	Wyoming	N
7	Missouri	Vermont	N
8	Illinois	Vermont	N
9	Missouri	Montana	Y
10	Illinois	Montana	Y
11	Louisiana	Rhode Island	N
12	Delaware	North Dakota	N
13	Pennsylvania	Maine	N
14	California	Wyoming	N
15	Illinois	Iowa	N
16	Illinois	Maine	Y
17	Massachusetts	South Dakota	N
18	California	Vermont	N
19	Virginia	Vermont	N
20	Tennessee	Maine	Y
21	Indiana	Vermont	N
22	Florida	North Dakota	N
23	Rhode Island	South Dakota	N
24	Alabama	Utah	Y
25	Texas	North Dakota	N
26	Alabama	Rhode Island	Y
27	Kentucky	North Dakota	N
28	Illinois	Idaho	Y
29	Mississippi	Idaho	N
30	Pennsylvania	Utah	N
31	Pennsylvania	Rhode Island	N
32	Pennsylvania	Minnesota	Y
33	Missouri	Utah	N
34	Missouri	Rhode Island	Y
35	Illinois	Rhode Island	Y
36	Ohio	Vermont	N
37	Illinois	Minnesota	N
38	Mississippi	Rhode Island	Y
39	Arizona	Vermont	N
40	California	Idaho	N
41	Georgia	Rhode Island	Y
42	Tennessee	Rhode Island	N
43	New Jersey	Wyoming	N
44	Illinois	Colorado	Y
45	Ohio	Maine	N
46	Arizona	Maine	N
47	Virginia	Rhode Island	Y
48	Delaware	Rhode Island	N
49	Alabama	Connecticut	N
50	Virginia	Colorado	N

Table C.3: Potential ties of state-to-state influence ranked by $T_{ij} - T_{ij}^{PGH}$.

Table D.1: Estimated parameter entries of $\vec{\theta}$ and their corresponding standard errors (in parenthesis), for Model 9 fitted to inferred networks of influence with varied edge density (10%-15%); p values are denoted by *** for < 0.001, ** for < 0.01, and * for < 0.05, respectively; Reference AIC is obtained by fitting a model with only *edges* term to the corresponding network; see Section 6.2.1 for the definitions of model terms.

Model statistics	**network 1 (10%)**	**network 2 (11%)**	**network 3 (12%)**	**network 4 (13%)**	**network 5 (14%)**	**network 6 (15%)**
edges	-3.812(0.544)***	-3.815(0.507)***	-3.682(0.501)***	-3.719(0.477)***	-3.768(0.490)***	-3.886(0.487)***
mutuality	1.013(0.259)**	0.702(0.248)**	0.722(0.234)**	0.744(0.227)**	0.693(0.218)**	0.495(0.212)*
gwesp	0.592(0.085)***	0.611(0.083)***	0.614(0.084)***	0.595(0.613)***	0.565(0.083)***	0.630(0.086)***
out-edges : PGH	1.468(0.701)*	1.334(0.684)	1.263(0.642)*	1.216(0.613)*	1.252(0.619)*	1.398(0.596)*
in-edges : PGH	-1.249(0.625)*	-1.082(0.584)	-1.051(0.582)	-0.949(0.553)	-0.816(0.545)	-0.915(0.544)
out-edges : FLS	0.017(0.007)**	0.015(0.006)*	0.016(0.006)*	0.016(0.006)*	0.016(0.006)**	0.012(0.006)*
in-edges : FLS	-0.012(0.007)	-0.012(0.007)	-0.012(0.007)	-0.012(0.007)	-0.014(0.007)*	-0.013(0.007)*
edge covariate : CTI	0.414(0.273)	0.565(0.262)*	0.537(0.251)*	0.616(0.252)*	0.577(0.241)*	0.575(0.238)*
no shared border	0.335(0.255)	0.363(0.256)	0.223(0.224)	0.258(0.234)	0.339(0.241)	0.425(0.230)
AIC	1451	1554	1641	1732	1825	1905
AIC reference	1530	1633	1727	1820	1906	1991

Table D.2: Estimated parameter entries of $\vec{\theta}$ and their corresponding standard errors (in parenthesis), for Model 9 fitted to inferred networks of influence with varied edge density (16%-20%); p values are denoted by *** for < 0.001, ** for < 0.01, and * for < 0.05, respectively; Reference AIC is obtained by fitting a model with only *edges* term to the corresponding network; see Section 6.2.1.

Model statistics	network 7 (16%)	network 8 (17%)	network 9 (18%)	network 10 (19%)	network 11 (20%)
edges	-3.655(0.451)***	-3.608(0.472)***	-3.535(0.458)***	-3.253(0.477)***	-3.238(0.504)***
mutuality	0.597(0.201)**	0.554(0.198)**	0.543(0.184)**	0.617(0.186)***	0.494(0.178)**
gwesp	0.662(0.089)***	0.624(0.089)***	0.603(0.095)***	0.546(0.098)***	0.544(0.104)***
out-edges : PGH	1.642(0.570)**	1.657(0.574)**	1.605(0.542)**	1.741(0.562)**	1.680(0.557)**
in-edges : PGH	-1.367(0.525)**	-1.360(0.534)*	-1.296(0.526)*	-1.603(0.519)**	-1.531(0.512)**
out-edges : FLS	0.012(0.006)*	0.012(0.006)*	0.012(0.006)*	0.011(0.006)	0.010(0.006)
in-edges : FLS	-0.015(0.006)*	-0.015(0.007)*	-0.018(0.008)**	-0.018(0.006)**	-0.018(0.006)**
edge covariate : CTI	0.517(0.229)*	0.540(0.232)*	0.574(0.231)*	0.598(0.238)*	0.554(0.230)*
no shared border	0.305(0.212)	0.342(0.214)	0.360(0.207)	0.326(0.212)	0.415(0.201)*
AIC	1970	2059	2134	2211	2282
AIC reference	2069	2147	2218	2290	2355

6.5 Appendix E: U.S. state ranking by nodal attributes

We provide U.S. state rankings in terms of states' nodal attribute values. Here we have five separate rankings, one for each of the nodal attributes {PGH, MHI, PPL, FLS, and CTI}, see Table E.1, Table E.2, Table E.3, Table E.4, and Table E.5). When a state ranks 1 on a list, this indicates that the state has the largest nodal attribute value in the country, while rank 49 corresponds to the smallest value of the nodal attribute (Hawaii is excluded from this study). On these tables we also provide in the third column the net out-degree of each state as measured by the difference of outgoing edges and incoming edges. States with larger net out-degrees take more of a leader role than a follower role.

Rank	State	Outgoing edges - Incoming edges in y^*
1	Louisiana	3
2	Alabama	-4
3	Michigan	0
4	Pennsylvania	1
5	Missouri	7
6	Illinois	16
7	Mississippi	0
8	Georgia	6
9	Maryland	0
10	Tennessee	3
11	California	0
12	North Carolina	2
13	Virginia	-1
14	South Carolina	6
15	Delaware	1
16	Indiana	5
17	Arkansas	3
18	Florida	7
19	Ohio	-6
20	Texas	-5
21	Kansas	-4
22	Arizona	-10
23	Kentucky	2
24	Wisconsin	-4
25	New Jersey	-2
26	Connecticut	-4
27	Oklahoma	7
28	Nevada	-2
29	West Virginia	0
30	Nebraska	4
31	Colorado	1
32	Massachusetts	7
33	New York	-2
34	Washington	-2
35	Alaska	-6
36	Minnesota	5
37	Rhode Island	5
38	Utah	4
39	Oregon	-3
40	Idaho	-8
41	New Mexico	-5
42	Maine	0
43	Iowa	-1
44	Montana	-5
45	Vermont	-5
46	New Hampshire	-13
47	Wyoming	-5
48	North Dakota	2
49	South Dakota	0

Table E.1: U.S. states ranked by PGH.

Rank	State	Outgoing edges - Incoming edges in y^*
1	Maryland	0
2	New Hampshire	-13
3	Connecticut	-4
4	New Jersey	-2
5	Alaska	-6
6	Minnesota	5
7	Massachusetts	7
8	Virginia	-1
9	Colorado	1
10	Utah	4
11	Washington	-2
12	California	0
13	Delaware	1
14	Rhode Island	5
15	Illinois	16
16	Wisconsin	-4
17	Vermont	-5
18	Nebraska	4
19	Nevada	-2
20	Oregon	-3
21	Iowa	-1
22	Wyoming	-5
23	Pennsylvania	1
24	New York	-2
25	Michigan	0
26	Missouri	7
27	North Dakota	2
28	Kansas	-4
29	Texas	-5
30	Arizona	-10
31	Ohio	-6
32	Idaho	-8
33	Georgia	6
34	South Dakota	0
35	Indiana	5
36	Maine	0
37	Florida	7
38	North Carolina	2
39	South Carolina	6
40	Oklahoma	7
41	Montana	-5
42	Tennessee	3
43	New Mexico	-5
44	Alabama	-4
45	Kentucky	2
46	Louisiana	3
47	Arkansas	3
48	West Virginia	0
49	Mississippi	0

Table E.2: U.S. states ranked by MHI.

Rank	State	Outgoing edges - Incoming edges in y^*
1	California	0
2	Texas	-5
3	New York	-2
4	Florida	7
5	Illinois	16
6	Pennsylvania	1
7	Ohio	-6
8	Michigan	0
9	Georgia	6
10	North Carolina	2
11	New Jersey	-2
12	Virginia	-1
13	Washington	-2
14	Massachusetts	7
15	Indiana	5
16	Tennessee	3
17	Arizona	-10
18	Missouri	7
19	Maryland	0
20	Wisconsin	-4
21	Minnesota	5
22	Colorado	1
23	Alabama	-4
24	Louisiana	3
25	South Carolina	6
26	Kentucky	2
27	Oregon	-3
28	Oklahoma	7
29	Connecticut	-4
30	Iowa	-1
31	Mississippi	0
32	Arkansas	3
33	Kansas	-4
34	Utah	4
35	Nevada	-2
36	New Mexico	-5
37	West Virginia	0
38	Nebraska	4
39	Idaho	-8
40	Maine	0
41	New Hampshire	-13
42	Rhode Island	5
43	Montana	-5
44	Delaware	1
45	South Dakota	0
46	Alaska	-6
47	North Dakota	2
48	Vermont	-5
49	Wyoming	-5

Table E.3: U.S. states ranked by PPL.

Rank	State	Outgoing edges - Incoming edges in y^*
1	California	0
2	Massachusetts	7
3	Illinois	16
4	New Jersey	-2
5	Connecticut	-4
6	Rhode Island	5
7	New York	-2
8	Pennsylvania	1
9	Maryland	0
10	North Carolina	2
11	Michigan	0
12	Florida	7
13	Delaware	1
14	Virginia	-1
15	Nebraska	4
16	Tennessee	3
17	Nevada	-2
18	Utah	4
19	Indiana	5
20	Arizona	-10
21	Oklahoma	7
22	Ohio	-6
23	Oregon	-3
24	Iowa	-1
25	Missouri	7
26	Wisconsin	-4
27	Washington	-2
28	Georgia	6
29	Minnesota	5
30	Colorado	1
31	West Virginia	0
32	Arkansas	3
33	Idaho	-8
34	New Hampshire	-13
35	Texas	-5
36	North Dakota	2
37	South Carolina	6
38	Louisiana	3
39	Alaska	-6
40	Mississippi	0
41	Maine	0
42	Kentucky	2
43	New Mexico	-5
44	Montana	-5
45	Alabama	-4
46	Kansas	-4
47	Wyoming	-5
48	South Dakota	0
49	Vermont	-5

Table E.4: U.S. states ranked by FLS.

Rank	State	Outgoing edges - Incoming edges in y^*
1	Vermont	-5
2	Rhode Island	5
3	Massachusetts	7
4	Connecticut	-4
5	Maine	0
6	New York	-2
7	Maryland	0
8	Delaware	1
9	New Jersey	-2
10	Oregon	-3
11	Illinois	16
12	West Virginia	0
13	California	0
14	Michigan	0
15	New Mexico	-5
16	Pennsylvania	1
17	Washington	-2
18	Minnesota	5
19	Wisconsin	-4
20	North Dakota	2
21	Nevada	-2
22	Ohio	-6
23	Montana	-5
24	Colorado	1
25	New Hampshire	-13
26	Virginia	-1
27	North Carolina	2
28	Iowa	-1
29	Florida	7
30	Missouri	7
31	South Dakota	0
32	Alaska	-6
33	Arizona	-10
34	Indiana	5
35	South Carolina	6
36	Texas	-5
37	Arkansas	3
38	Georgia	6
39	Tennessee	3
40	Mississippi	0
41	Louisiana	3
42	Alabama	-4
43	Kentucky	2
44	Kansas	-4
45	Nebraska	4
46	Utah	4
47	Wyoming	-5
48	Oklahoma	7
49	Idaho	-8

Table E.5: U.S. states ranked by CTI.

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