What factors drive state firearm law adoption? An application of Exponential-family random graph models

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Abstract

Guns are a ubiquitous feature of contemporary US culture, driven, at least partly, by firearms' constitutional enshrinement. However, the majority of laws intended to restrict or expand firearm access and use are formulated and passed in the states, leading to 50 different firearm-related legal environments. To date, little is known about why some states pass more restrictive or permissive firearm laws than others. In this article, we identify patterns of firearm law adoption across states, by framing the problem as a bipartite network (states connected to laws and laws connected to states) that is the result of a complex, and interconnected system of unobserved forces. We employ Exponential-family Random Graph Models (ERGMs), a class of statistical network models that allow for the dispensing of the assumptions of statistical independence, to identify factors that increase or decrease the likelihood of states adopting permissive or restrictive firearms laws over the period 1979 to 2020. Results show that more progressive state governments are associated with a higher chance of enacting restrictive firearm laws, and a lower chance of enacting permissive ones. Conservative state governments are associated with the analogous reversed association. States are more likely to adopt laws if bordering states have also adopted that law. For both restrictive and permissive laws the presence of a law in a neighboring state increased the conditional likelihood of a state having that law, that is laws diffuse across state borders. High levels of homicides are associated with a state having adopted more permissive, but not more restrictive, firearm laws. In summary, these results point to a complex interplay of state internal and external factors that seem to drive different patterns of firearm law adoption Based on these results, future work using related classes of models that take into account the time evolution of the network structure may provide a means to predict the likelihood of future law adoption.

1 INTRODUCTION

In 2019 the US experienced 39,707 firearm-related deaths (12.2 per 100,000 population), or approximately 109 per day (Xu et al., 2021). Firearm-related deaths account for 16.4% of all injury-related deaths in the U.S; among them, 96.5% are caused intentionally, of which about one-third are due to homicide and 60.0% from suicide (Xu et al., 2021) These figures place the U.S. as the high-income country with the highest firearm homicide and suicide rates (Grinshteyn and Hemenway, 2016). For initial hospitalization alone, firearm-related harms cost on average $734 million per year (Spitzer et al., 2017). In addition to hospitalization, firearm-related harms incur other costs, such as rehabilitation, long-term care, criminal justice, job loss, and mental health treatments. The yearly total cost associated with firearm-related injuries is $174 billion, or $564 per American (Pacific Institute for Research and Evaluation, n.d.).

Despite concern over gun violence and its profound effects, regulation of firearms remains one of the most divisive topics in the U.S. The right to keep and bear arms is protected by the Second Amendment, and federal statutes regulate the manufacture, trade, possession, transfer, record keeping, transport, and destruction of firearms, ammunition, and firearm accessories. The major federal gun law is the 1993 Brady Handgun Violence Prevention Act (Congress, 1994), which mandated federal background checks on firearm purchases. However, because each state may pass its own laws that regulate firearm ownership, there are 50 highly divergent firearm regulatory environments in the U.S. Specific firearm-related laws vary substantially from state to state, so that some states have much stricter regulations on purchasing, permitting, carrying, and storing firearms, while other states provide firearm owners greater legal protections through so-called "stand your ground" and other laws. To further complicate the issue, reciprocity of laws between states is rare. For example, Vermont recognizes a New York permit, but New York does not recognize a Vermont permit.

There is a long history of research showing that U.S. states tend to be either policy innovators or policy laggards (Elazar, 1972). Some researchers have attributed these variations to relatively consistent political cultures, which helps to explain why some states adopt policies that tend to be more "conservative" or "liberal" (Berry et al., 1998; Elazar, 1972; Erikson et al., 1993). But researchers have increasingly focused on inter-state dynamics in search of an explanation for the spread of public policies over time (Gray, 1973; Walker, 1969). One branch of this literature suggests that states define their policy choices in relation to neighboring states in order to increase economic competition or to decrease in-migration of poor or "undesirable" residents from neighboring states (Bailey and Rom, 2004; Peterson and Rom, 1990; Saavedra, 2000; Volden, 2002). Another related theme has been characterized as "policy learning" wherein state legislators may look to states that are similar to their own (or that have confronted similar policy challenges) for seemingly effective solutions to an existing problem (Boehmke and Witmer, 2004). See Mooney (2021) for a recent review of this literature.

Firearm laws are only one set of public policies that mostly play out at the state level. Studies of policy diffusion have often focused on health and safety-related laws, given the US Constitution's granting of powers to states to protect citizens' health and safety (Gostin and Wiley, 2016). An early study on the State Child Health Insurance Program (CHIP) showed that an important characteristic of the policy (whether or not it was effective in lowering child uninsurance rates) was a consistent predictor of subsequent policy adoptions (Volden, 2006). Internal state factors associated with policy adoption included having the state legislature and governor affiliated with the same political party and higher income per capita, while factors negatively associated with policy adoption included whether the states differed significantly in terms of their population, ideology, and economy (Volden, 2006). Studies on alcohol and driving safety policies confirmed the importance of ideological similarity, geographic adjacency, and added the role of lobbying groups such as Mothers Against Drunk Driving (MADD) in predicting which states would be most likely to adopt new motor vehicle safety laws (Abaid et al., 2015; Anderson et al., 2016; Grabow et al., 2016; Yu et al., 2020). Studies of the diffusion of state tobacco regulation similarly identified the role of neighboring states and a set of internal drivers, including the state's ideological orientation, state legislative professionalism, whether branches of state government were politically unified, and similarities in government capacity and resources between the original state and those subsequently adopting the same laws (Shipan and Volden, 2014).

However, the firearm regulatory environment is arguably one of the more complex and dynamic ones faced by state legislators because the topic is highly politicized, there are a number of powerful lobbying and advocacy groups involved, and evidence on best practices is often lacking (Carlson, 2020). Objections to policy approaches to regulation of alcohol or tobacco were often framed in terms of whether government regulation was justified or effective, not that such products were not harmful. But public discourse on solving the problem of firearm-related violence has not reached consensus on whether the most effective approach to reducing such harms would be accomplished by having more or by having fewer firearms. This lack of consensus may be due to the fact that empirical evidence for best practices in firearm law is often lacking (Smart et al., 2020). While this evidence gap has been attributed in part to the lack of federal funding to conduct large-scale rigorous studies (Morrall, 2018), other factors such as the fact that firearm sales can actually increase prior to new regulatory efforts (Jones, 2015) makes assessment of the causal impact of firearm legislation especially challenging.

Given this context, it is not clear if the diffusion of firearm laws would be explained by the most commonly identified drivers of policy diffusion in other policy realms. Existing studies on the topic have, to date, focused on single firearm laws such as concealed weapons (Tucker et al., 2012) and stand your ground laws (Butz et al., 2015). From these studies emerge the importance of neighboring state policy adoption in dealing with what the authors term "trans-boundary policy problems" such as carrying concealed weapons across state lines (Tucker et al., 2012). However, Butz et al. (2015) state that the results of their study of the diffusion of state stand your ground laws "exhibits atypical and complex patterns of diffusion not observed in previous studies." It is also unclear from the literature whether adoption of more restrictive firearm laws would follow the same pattern as seen for more permissive ones.

This study departs from the approach taken by previous works by framing states and firearm laws within a network setting, where a state's interactions with other states and with firearm policies is explicitly modeled using Exponential-family Random Graph Models (ERGM) for the period 1970-2020. Using the ERGM approach removes important statistical assumptions of independence while allowing for identification of internal and external drivers of the diffusion of state firearm regulations. A further objective is to test whether such predictors differ based on whether the law in question is classified as restrictive or permissive of firearm acquisition and use. By simultaneously modeling the spread of laws that either restrict or enable firearm access and use, we seek to probe more directly concerns about how much the political characterization of a law (or its possible effects) may influence its diffusion to other states.

2 MATERIALS AND METHODS

2.1 Data

For our study we used the RAND Corporation's State Firearm Law Database, one of the most comprehensive and recent compilations of state firearm laws collected through original legal research methods (Cherney et al., 2020). Each line in this dataset is a single legislative action, carried out by a single state, at a single point in time. A legislative action is defined either as the enactment of a new law, or the repeal or modification of an existing one. We restricted the data to the period from January of 1979 to January of 2020, resulting in 918 events representing new firearm laws or changes to existing laws over the period.

RAND has categorized each firearm law into 17 broad topic areas (e.g. Child Access Protection, Waiting periods, Background checks, Stand your ground, concealed carry) and also identified each individual law as either "Permissive" (meaning it makes firearm access or use easier, such as concealed carry laws) or "Restrictive" (meaning it limits some aspect of firearm access or use, such as waiting periods and background checks). We believe that the legislative processes driving permissive and restrictive laws are likely to be different. For this study, we consider properties that are separately associated with the adoption of both permissive and restrictive laws. We do not estimate covariate effects for the individual law categories, as there are only 50 states, rather we consider the whole state firearms law environment to understand the types of states that adopt broadly permissive or restrictive laws.

Figure 5.1 shows the state map for both permissive and restrictive state laws. The colors correspond to the number of categories as defined by RAND, in which each state has a law. Note for restrictive laws, California and Connecticut have the most categories of laws, while for permissive laws both Utah and Georgia have the most categories of laws.

In terms of state covariates, we base our selection on previous research and include shared borders based on geographic adjacency, and yearly measures of the following: government and citizen ideology using Berry's state policy scales in which 0 represents the most conservative and 100 the most liberal (Berry et al., 2010), homicides per capita from the CDC to represent the extent to which firearms may be on the state's policy agenda, firearm background checks per capita from the FBI in order to provide a proxy measure of the relative prevalence of firearms in the state, and the state population and income per capita from the US Census Bureau as measures of the state's resources. In sensitivity analyses we additionally test the Squire Index of state legislative professionalism which measures the extent to which state legislators receive a salary, have a professional paid staff, and the number of days the legislature is in session (Squire, 2017), the proportion of the population that is made up of young males (given they have the highest rate of death from firearm-related causes), and whether the state had (for that year) a government formed by a majority of the same political party in each legislature as the governor, given that under such a situation it should be easier to pass laws in general.

2.2 States and firearm laws as a bipartite network

Both theory and previous research support the contention that states do not act independently when enacting firearm-related legislation, even after accounting for states' similarities (Tucker et al., 2012). As a result we formulate a network of states in which each state's legislative actions can impact that of other states. In this setting our data become a single pooled observation of a complex process of states' legislative activity and interactions over four decades.

In order to understand states' interactions we could derive a network connecting states to other states. We could then consider the types of laws passed by states, and how their neighbors or other properties of such a network impact the types of laws they pass. However, how should we connect the states. Should geographically close states be connected? Should states with similar laws be connected? Should laws be connected based on substantive knowledge? In short there is no way to objectively define such a network. There has been some work to infer policy influence networks (Desmarais et al., 2015), however even these algorithms require subjective choices of parameters.

Therefore we consider the system as a bipartite network, where states can be connected to laws, but not to other states and where states form ties with a law category if they have adopted that law. States that are not connected to laws are defined as those who have not adopted that law. We consider the snapshot of the system at January 2020, that is, when a state adopted a law has no impact on our analysis.When states adopt a law, there is no reciprocal relationship since laws cannot adopt states. Thus the relationship between states and laws in not regarded as directed and this removes the requirement of subjective choices to derive the network.

Figure 5.3 shows the complete network, which cannot be easily visualised, due to the system's complexity. We will use network models to concretely and qualitatively unpack this complexity. A subset of the network is also shown, which emphasizes the bipartite setup of the data.

Projections of two-mode network data to one-mode data are common, though of course part of the data is lost. In our case projecting the two-mode network to a single network discards significant information. For example, as most states share many firearm laws, a large number of states would be connected with the standard for k=1 for the "shares k neighbors" projection. For higher values of k, few states would be connected. The choice of k dictates the sparsity of the network, and the information loss. As ERGMs can account for bipartite networks naturally through the choice of bipartite network statistics, we retain the bipartite structure. This setting allows for edges connecting states to laws, i.e. state law adoptions, that are dependent on the types of laws that other states have adopted. Including state covariate terms (e.g. political ideology, resources, and ideology) and state dyad covariate terms such as shared borders, allows for credible inference, without the need for independence assumptions.

This approach departs from the most common statistical method used to study policy diffusion across US states, event history analysis (EHA) (Boehmke, 2009) in several ways. First, EHA requires an assumption of independence, which we do not think can be justified given our dataset. Second, data for EHA diffusion analyses are usually set up dyadwise, that is the unit of observation is a pair of states, where diffusion of a law from the sender to the receiver is possible. Units are removed after the receiver has adopted the law. In our case as we have multiple laws, we would either need to consider triples of state-state-laws as units of observation or employ a multiple failure model, where each different law adoption is regarded as a "failure." Since there are multiple observations from the same state in this setup, cluster robust standard error estimation is often used in EHA, but this approach will produce more conservative results and does not fully account for highly complex dependencies between units and for this reason may still be biased.

2.3 Exponential-family random graph models (ERGMs)

Exponential-family Random Graph Models (ERGMs) Robins et al. (2007) are a flexible class of models developed for social network modeling, where there is strong dependence between stochastic ties among fixed actors. For a review paper on these models see Goldenberg et al. (2010) and Robins et al. (2007) and citations therein. The general setting is a fixed set of nodes or actors that connect to each other. The connections are regarded as random and represent some kind of social interaction. Such social interactions are usually strongly interdependent, e.g., in a friendship network it is often observed that friends of friends are much more likely to also be friends than some other arbitrarily selected node. The inherent phenomena that these models deal with is a fixed set of stochastic connections between actors, which are highly dependent on one another. In our case, these models serve as highly parsimonious representations of complex law-making processes.

We next define commonly used notation. We consider a fixed set of nodes $\{1, \ldots, n\}$ each with p fixed nodal covariates $\{X_1 \ldots, X_n | X_i \in \mathbb{R}^p\}$. We define y to be a graph on this fixed noted set, in particular, a graph realized from the random variable Y. Since we regard any nodal covariates as fixed, for a network of size n, Y takes values in the space $\mathcal{Y} = \{a \in \mathbb{R}^{n \times n} \quad | \quad \forall i, j \quad a_{i,i} = 0 \quad a_{i,j} \in \{0,1\}\}$. For undirected networks, the additional restriction that $a_{i,j} = a_{j,i} \quad \forall i, j$ is added. A dyad is defined to be any pair of nodes i,j. Note that the sample space, even in the restricted undirected case, is finite and of size $2^{\frac{n(n-1)}{2}}$; this becomes astronomically large even for small networks.

Equation (2.1) gives the formulation of ERGM as a standard exponential-family model, with the natural parametrisation, over the space $\mathcal{Y}$. We define the parameter $\theta \in \mathbb{R}^q$, with g as a mapping, $g: y \to \mathbb{R}^q$. In the exponential family framing $g(y)$ is a vector of sufficient statistics from the graph. These graph statistics may depend on both the random edges and the fixed covariates $\{X_i\}_{i=1}^{n}$, the dependence on the covariates is suppressed in the above since they do not vary between different realizations of y.

$$p(y|\theta) \quad = \frac{\exp\left(\theta^{\top} g(y)\right)}{Z(\theta, \mathcal{Y})} \qquad (2.1)$$

ERGMs are fully specified by the choice of statistics g, which the model user must specify. This task is analogous to model selection for a standard regression analysis. Typically researchers believe that characteristics of the nodes can impact the chance of an edge forming, e.g. the income of a state may be thought to be related to the chance of a state passing a restrictive law. However, the power of the model is that we can choose statistics to account for properties of the network that would be over or under represented by a model that assumed independence. For example it is typical in friendship networks to observe more triangles of friends than any dyad-independent model would produce, such behavior can be accounted for by the inclusion of a triangle count term in the ERGM specification, ensuring that the model places mass only on networks that have a similar triangle structure to the observed network. In our setting we expect pairs of states may share a number of laws, that cannot be accounted for by their similarity in characteristics alone. They share more laws, because in the social process, once one state adopts that law, the other state is more likely to adopt it, with probability above and beyond what can be expected due to their characteristic similarity. We can account for such behavior with structural ERGM terms.

In practice, ERGM models including graph subcounts are used to, in some sense, "account for the social structure." This allows for valid inference of the effect of nodal covariates on tie formation, without the need for an independence assumption.

There are various model selection paradigms that can be applied. For example, consideration of the AIC for different models or goodness of fit (GOF) statistics Hunter et al. (2008) derived from simulations, for some summary statistics of the simulated graphs. The GOF procedure favors models that produce graphs whose simulated distribution of summary statistics contains the observed graph summary statistics as plausible values.

$Z(\theta, \mathcal{Y})$ in Equation (2.1) is the usual exponential family normalizing constant i.e. $Z(\theta, \mathcal{Y}) = \sum_{y \in \mathcal{Y}} \exp\left(\theta^{\top} g(y)\right)$. The normalizing constant and hence the likelihood is intractable, for all but trivially small networks due to the high dimensional sum. As a result the model is usually fit using Markov Chain Monte Carlo (MCMC) methods to derive an MCMC Maximum Likelihood Estimate (MLE) (Hunter and Handcock, 2006).

The interpretation of its parameters is similar to that of a logistic regression, but one that requires conditioning on the rest of the graph. We define $y_{i,j}^{c}$ as the graph y without the dyad (i,j). The log odds of the presence of a edge between node i and j depends on the change statistics $\delta(y_{i,j}) = g(y_{i,j}^{+}) - g(y_{i,j}^{-})$, the difference in the graph statistics resulting from toggling the edge (i,j) on. $y_{i,j}^{+}$ is the graph y with the edge (i,j) toggled on and $y_{i,j}^{-}$ with it toggled off. The log odds ratio is shown in equation (2.2).

$$\frac{\operatorname{logit}\left(p\left(y_{i,j}=1 \mid \theta, y_{i,j}^{c}\right)\right)}{\operatorname{logit}\left(p\left(y_{i,j}=0 \mid \theta, y_{i,j}^{c}\right)\right)}=\theta^{\top} \delta\left(y_{i,j}\right) \qquad (2.2)$$

Typically, counts of subgraphs are included such as triangles, stars etc., to allow for the social structure of the problem. For example the qualitative interpretation of a positive triangle term would be that "conditional on the rest of the network, if an edge completes a triangle it is more likely to form than if it did not complete a triangle." Thus a positive triangle parameter suggests social transitivity above what would be expected based on other parameters.

Unfortunately, in almost all real data cases we cannot include simple terms such as triangles and stars, as they result in so called near degeneracy (Handcock, 2003). We instead include geometrically weighted analogues (Hunter and Handcock, 2006), which are more complex but are often regarded with broadly similar qualitative interpretations. For example a model with a positive geometrically weighted edgewise shared partner term is regarded as having a tendency for social transitivity, but up to some limit. Not every triad is likely to be completed, this limits the explosive tendency of triangle terms.

For our setting we need to specify appropriate ERGM statistics to take account of two mode nature. Appropriate statistics essentially allow edges to form only between laws and states, enforcing the bipartite nature of the data. For example usually geometrically weighted edgewise shared partner terms are included to account for transitivity, the analogue in our bipartite case are geometrically weighted dyadwise shared partners (GWDSP), which account for states tendency to adopt laws that other states have also adopted.

For example our interpretation of positive a state-dyadwise shared partner parameter, is that conditional on the rest of the network, a tie that results in a pair of states sharing a law is more likely to have formed, that if it did not result in a pair of states sharing a law.

3 RESULTS

We first describe the dataset and note that the adoption of laws varies significantly over time, with different laws being more prevalent among different states during various time periods. Figure 5.2 shows the progression of law adoptions split by category for permissive and restrictive laws. We note that different categories of laws experienced more adoptions at different time periods. As mentioned above, our method only considers the full environment at January 2020; the timing the of the law adoption does not impact our analysis, only the laws that states have adopted by the end of the period of observation.

3.1 Network data description

Figure 5.3 shows the bipartite network of laws and states with states as circles colored blue, permissive laws green and restrictive laws red squares. This plot is based on all laws that are contained in the RAND dataset. There are 51 states (full states and District of

Columbia) and 21 law categories, of which 10 are permissive and 11 are restrictive. Thus there are $51 * 21 = 1071$ possible edges of which 467 are observed up to 2020.

Figure 5.4 shows the distribution of degree for both the states and laws in the network. State degree is the number of laws a state has adopted. Law degree is the number of states that have adopted a law.

Figure 5.4 also shows the distributions of dyadwise shared partners. Dyads are in this case a pair of states or a pair of laws, so a state-dyadwise shared partner value of 1 would be a pair of states sharing a single law, a state-dyadwise shared partner value of 3 would be a pair of states sharing 3 laws.

Degree distributions and DSP distributions are key properties of the firearms law environment. The state degree distribution represents the range of numbers of laws that states adopt, and the law degree distribution represents the range of popularity of different laws. The distribution of state degrees and law degrees are, as expected, quite different. The DSP distributions represent the extend to which states share laws with other states, and pairs of laws are adopted by the same state.

3.2 Predictors of state firearm law adoption

Table 5.1 shows the results of a set of nested ERGM models, including progressively more covariates. The edges, GW state DSP, and GW law DSP, are purely structural terms relating only to the edges in the network. The edge parameter accounts for baseline density and is similar to an intercept in a regression analysis. The remaining model terms relate to nodal covariates. We considered government ideology (gov idea), shared borders, homicides per capita (homicides), firearm background checks per capita (backgrounds), raw state population (population), citizen ideaology (cit idea) and income per capita (income).

The Akaike Information Criterion (AIC) is presented for a comparison of model fit. As presented in the table, including all terms available resulted in the best fitting mode, that is, the one with the lowest AIC. We chose model covariates, approximately in the order of our own perceived likelihood of their importance in predicting state law adoption. We also considered adding other covariates as described in the appendix. Table 7.1 shows the results of including these covariates. While the AIC was slightly improved, the fits did not alter our qualitative conclusions. Note we explicitly do not discuss our results in terms of statistical significance in line with best practice recommendations (Wasserstein and Lazar, 2016).

The results show ideology is related to the presence of both permissive and restrictive laws. Higher values of government ideology (more liberal governments) are associated with a higher chance of enacting restrictive laws, and a lower chance of enacting permissive laws, with the corresponding reversal for lower value of government ideology (more conservative states). Note that in model 5 and 6 due to increased variability in the sampling distribution of the ideology parameters, it is not possible to identify which of citizen ideology or government ideology is the best predictor. The increased sample distribution variability in these parameters is due to their high correlation in the data.

All else equal, restrictive laws are not more likely to be enacted than permissive laws. Positive GW state DSP parameters with low sampling distribution variability, across all models suggest that pairs of states are more likely to adopt the same law, all else equal. Conversely the GW law DSP parameter estimates suggest that pairs of laws are less likely to be adopted, all else equal.

States sharing borders was important in all models, it is unlikely we would observe this dataset if there were truly a small state border effect. This suggests that states are more likely to adopt a firearm law if their bordering states have also adopted that law. When assuming heterogeneous effects for permissive and restrictive laws, both restrictive and permissive ones are likely to diffuse across state borders.

High levels of homicides per 100,000 population have an association with restrictive firearms laws in models 5 and 6. The relatively high p-value suggests less confidence in this association that the others. Homicides are not associated with restrictive laws. We note that homicides are mildly correlated with citizen ideology, so there is a likely a complex mechanism at play, which increases the variability in the estimates when both are included.

The number of gun background checks per capita is not associated with any legislative activity. State population size has an association with restrictive, but not permissive, firearms laws, but state income is not shown to be associated with any legislative activity.

3.3 Goodness of fit analyses

Following Hunter et al. (2008), we compare the observed values of important graph statistics to the distributions of those statistics derived from simulations on networks from our fitted model 7 shown in Table 5.1. As justification for the network approach we also compare the goodness of fit with a logistic regression model with the same dyad independent parameters shown in Table 5.1. That model assumes dyad independence, and its poor fit implies that the data are not independent, providing further justification for the ERGM approach.

In general the ERGM models as shown in Figure 5.5 fit the observed data well, that is, the majority of observed statistics could have been observed if the data generating process was indeed the fitted ERGM. Or particularly for the state DSP distribution, our fitted model generates simulated networks that have pairs states sharing a similar number of laws, as in the observed data

The state-degree distribution, was in general difficult to fit very well with either model, perhaps reflecting the complexity of the system or the differences between states not captured by the model covariates. The state-DSP and law-DSP distributions were much better fit with the ERGM, while the independent model did not capture the observed distribution at all. Together this reflects that simulated realizations from the dyad independent model fail to recreate important structures in the data. Due to this failure to recreate the observed data, any conclusions derived from the dyad independent model should be regarded with suspicion, as the model does not fit the data.

4 DISCUSSION

This study applied a novel network analysis method to identify factors associated with state adoption of different classes of firearm laws. Substantive results largely confirm a set of covariates associated with the adoption of permissive firearm laws (more conservative government and citizen ideology) as well as more restrictive ones (more progressive government and citizen ideology, and population size where more populous states are more likely to adopt restrictive laws than less population ones). Results also suggest that it may be necessary to take into account the interdependence of states when attempting to infer characteristics that may drive state law adoption. State borders were important for the adoption of both classes of laws as were the network connections formed as states adopted similar laws.

This study also demonstrated the poor fit on network statistics of a dyad independent model; to our knowledge nearly all prior studies of firearm policy diffusion have used dyad independent approaches. A dyad independent (logistic) model does not capture key features of the data that are important in understanding the types of firearm laws that states have passed. In particular the failure of the dyad independent model to take into account the complex and interdependent nature of the state law making process results in implausible simulated values. This suggests that future work on state law adoption and diffusion should similarly take into account the complex, dependent nature of law adoption, although it is unknown if such factors are equally important for other types of state laws, such as those related to nutrition, tobacco, or alcohol, among others.

While there are no studies to our knowledge that consider the entire state firearm law environment as a whole system, we believe the empirical results obtained here are largely consistent with the existing literature. In general, our method identifies broad predictors of firearm law adoption that apply to both law restrictive and permissive categories. Previous studies primarily focus on single laws, which may identify factors that can affect the likelihood of law adoption, for example some firearms laws are shown to be to likely diffuse across borders. This is in agreement with studies for other state laws considered as a whole system, e.g. impaired driving laws (Macinko and Silver, 2015), as well as a broad range of state policies across multiple domains (Boehmke and Skinner, 2011). When considering a study of the diffusion of single permissive firearm laws, the evidence is mixed. One study (Butz et al., 2015) found that shared borders were not associated with stand your ground (SYG) laws, whereas for concealed carry laws Tucker et al. (2012) found evidence of the importance of neighboring state adoptions. However, these single law category studies do not consider the rest of the firearm legal environment or take into consideration the complex network structure linking all 50 states.

More recently, there has been some work using network models to understand the flow of crime-related firearms between states, taking into account different state firearm legal environments. In one study, Takada et al. (2020) find that states with more restrictive firearm regulations are less likely than states with fewer firearm regulations to be the source of 100 or more firearms trafficked to the destination state. However, these more restrictive states were more likely to be the destination of trafficked firearms from less heavily-regulated states. In the only other application of ERGMs to the study of firearms, Andrade et al. (2020) much like Takada et al. (2020) assessed the spread of firearms across states with different levels of restrictive firearm laws and generally confirmed Tanaka's findings. The fact that more restrictive state legal environments may enhance the flow of firearms into that state from those with less restrictive laws further complicates the ability of existing statistical methods to identify a true causal effect of such laws on population health outcomes.

This study has several strengths and limitations. Framing the state firearms law legal environment as a bipartite network, allows for parsimonious modeling of the complex interactions between states. This yields an easily interpretable model, while improving model fit to the observed data with simulated data from our fitted model respecting the structure of the system. We suggest that this provides stronger evidence for the identified associations than do models that do not account for this structure.

However using ERGMs by no means removes the question of model mis specification. Our ERGMs are highly parsimonious, with the complex state legislative process being summarised by counts of sub-graphs of states and laws, as well as covariate effects limited to linear effects. This is likely to not be close to the true system generating process. Our interpretations are contingent on the data being generated from an ERGM, which is obviously not the case. Still, our approach is likely preferable to alternative approaches, as evidenced by our model's improved goodness of fit and the relaxing of assumptions regarding independence.

We also wish to highlight that due to the complexity of the system and the small sample size, no causal interpretation is made in this work. We interpret our results strictly as associations; current methods may be unable to unravel the true causal relationships for this highly complex system.

In addition, our approach considers a law adopted when just a single law in that category has been passed, thus the framing does not capture differences between specific state laws and their efficacy. There is a wide spectrum of laws in each category in terms of reach and impact and in our approach (as with many others), paradigm changing laws or inconsequential laws are treated the same.

Future work in this area includes testing the applicability of ERGM models in assessing policy adoption in realms that may be less politicized than firearms, such as tobacco regulation. Additionally, temporal exponential-family random graph models may provide additional insights in that they model the time evolution of the network as opposed to the static view provided by the ERGMs. Ultimately, causal models will be needed to understand the impacts of adoption of such laws on critical social issues, such as homicide and suicide, although given the complex legal environment and the lack of information on state variation in enforcement of such laws, the lack of "natural experiments," and small state sample size (50), this is likely to be difficult with current data and methods.

5 Tables and Figures

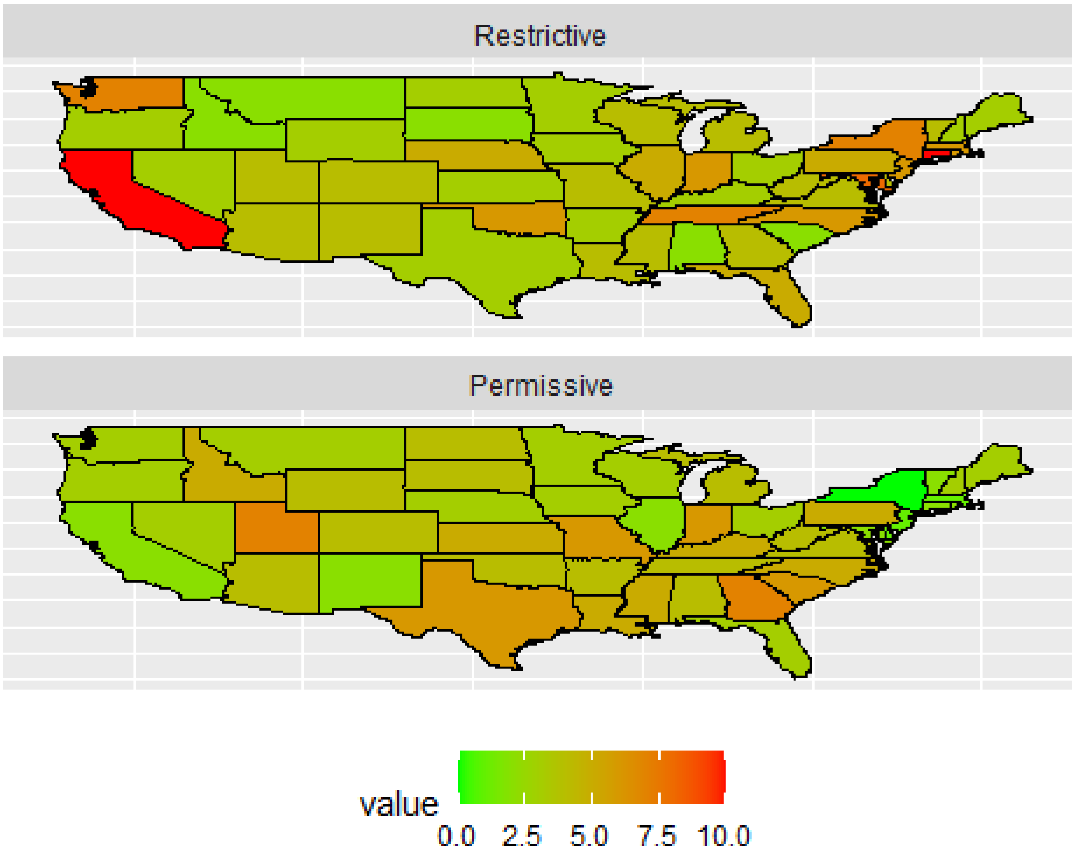

Figure 5.1: Map of the United States state firearm laws. Colors correspond with the raw number of the law categories in the RAND dataset that each state has adopted with green values representing fewer and red values representing greater numbers of laws.

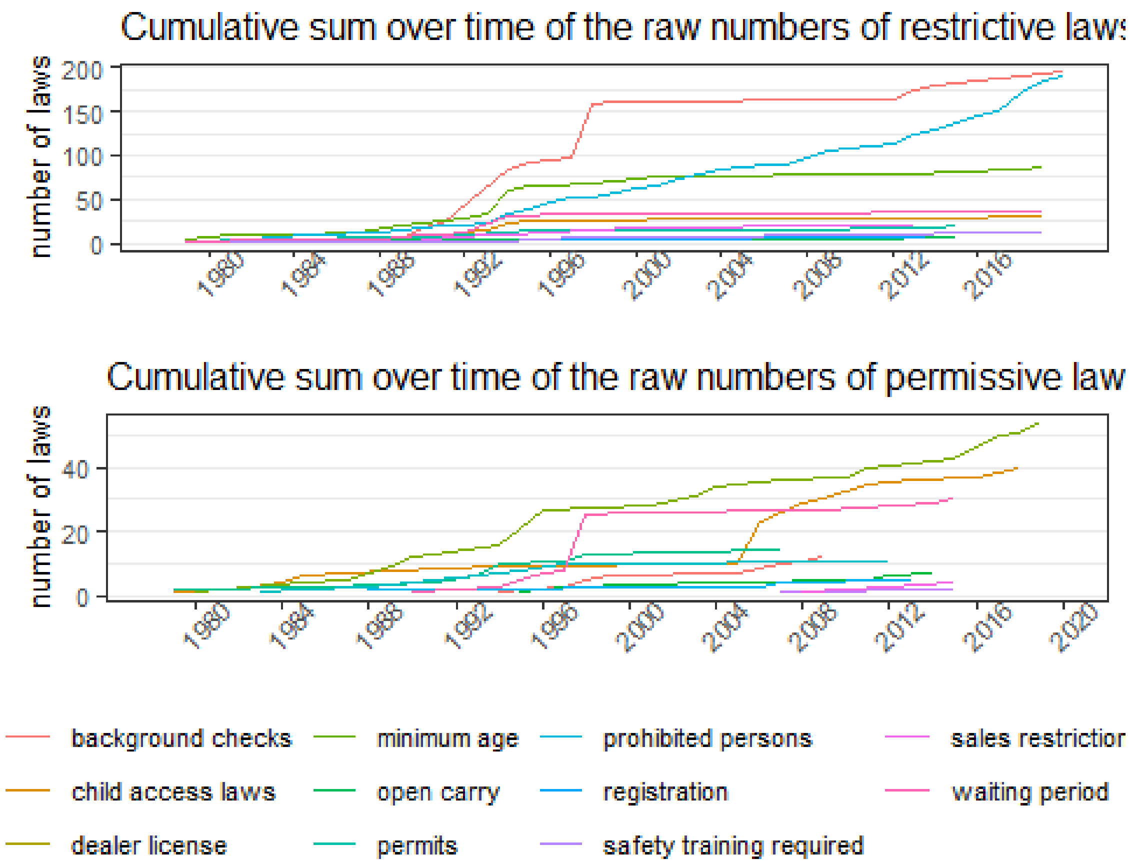

Figure 5.2: Progression of the cumulative sum of the numbers of permissive and restrictive laws passed.

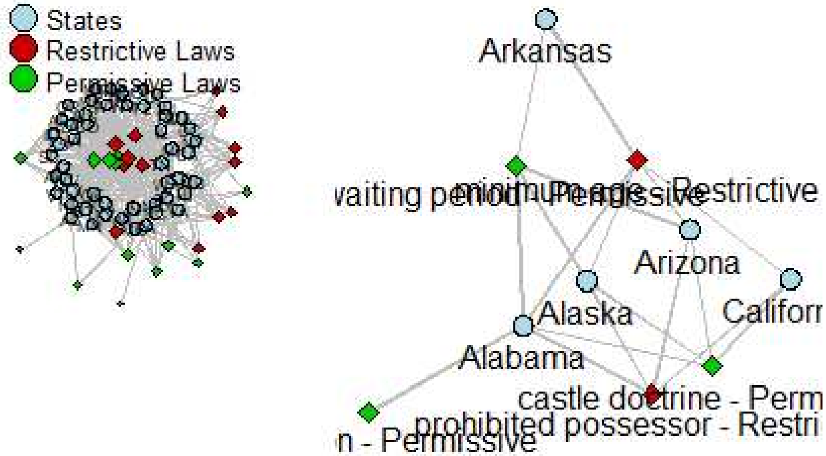

Figure 5.3: Plot of bipartite network of states adopting permissive and restrictive laws (left), and a magnified snapshot of one part of this network (right),

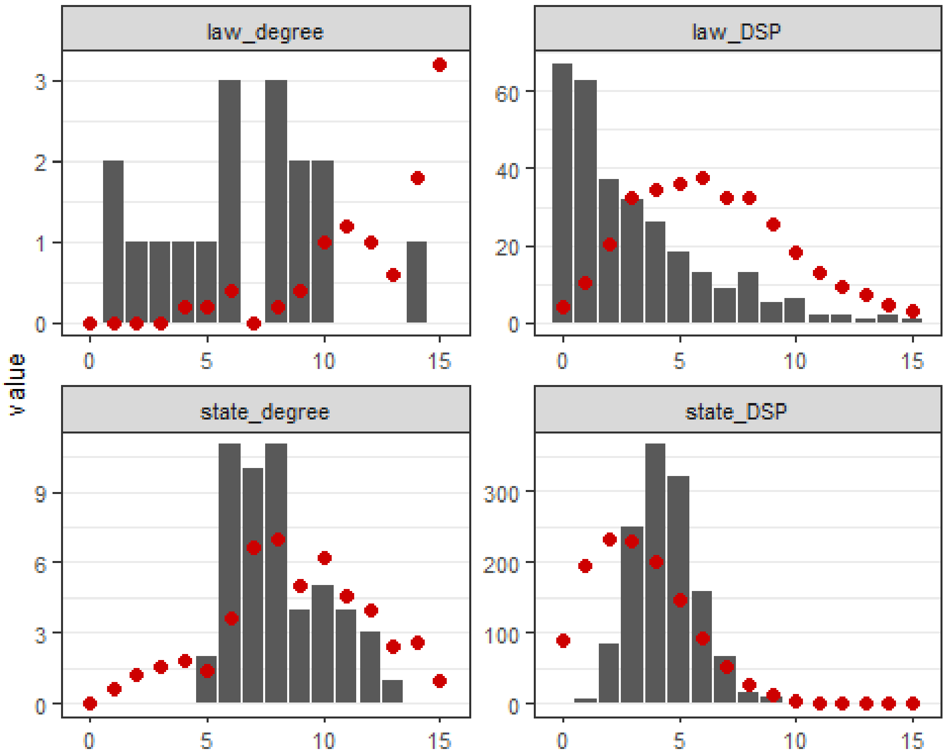

Figure 5.4: Barplot of the state and law degree and DSP distributions, red points denote the mean of a simple Bernoulli model for law adoption, which treats the dyads as independent. On each measure the simulated distribution is different from the observed distribution. In particular the DSP distribution is poorly recreated, suggesting that the dyad independent model does not capture important netowrk structure, i.e. the number of laws pairs of states tend to share, and the number of states that adopt pairs of laws.

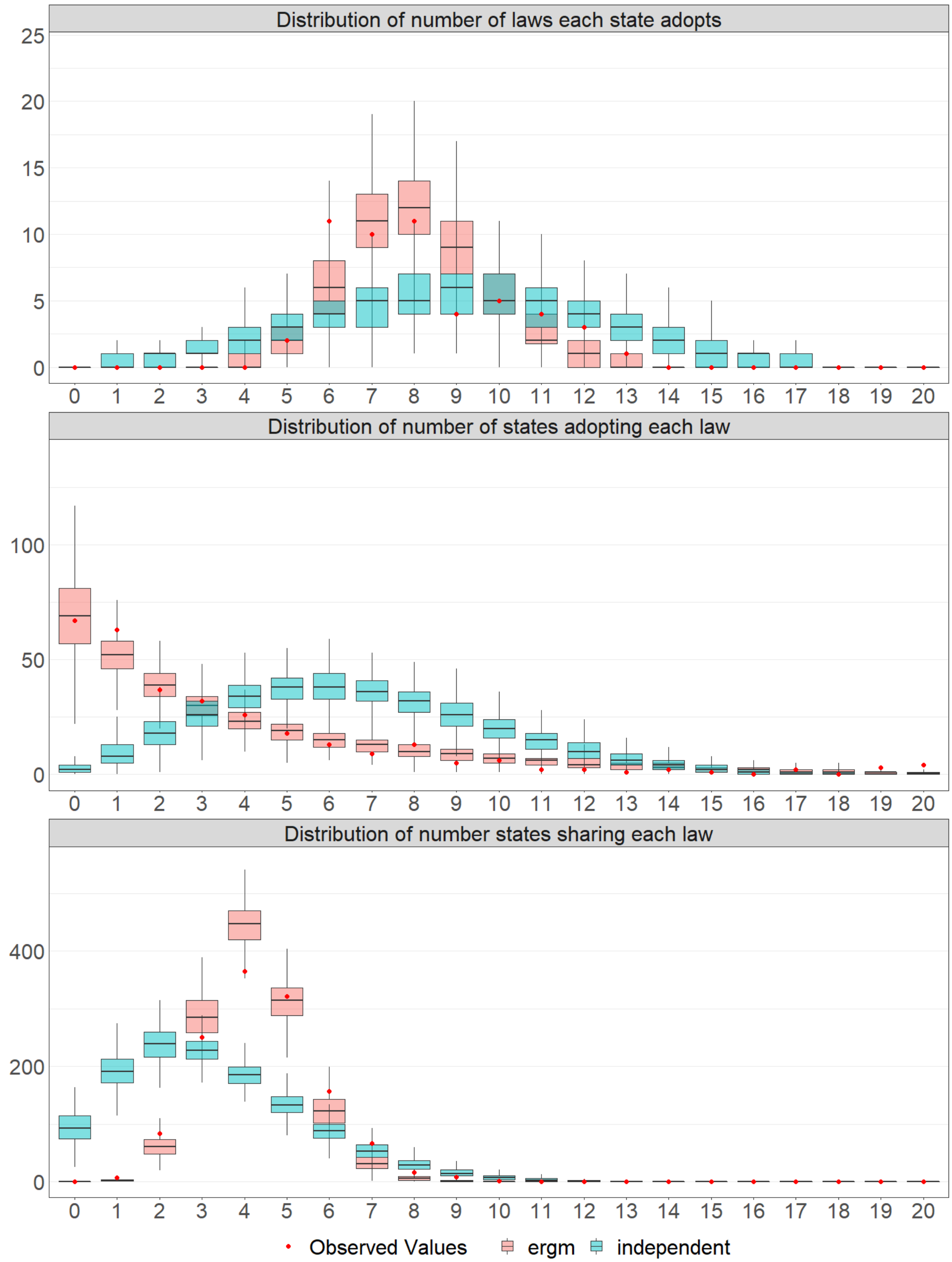

Figure 5.5: Goodness of fit plots of simulated distributions of law and state degree and DSP for the full ERGM model and logistic regression (independent) model. The ERGM model fits better on all distributions, in particular the DSP distributions where the logistic regression model simulated very different distributions of network statistics.

Table 5.1: Model Summaries for nested ERGM fits.

parameter[1]	logistic	model 1	model 2	model 3	model 4	model 5	model 6	model 7
edges	-2.05***	-1.94***	-1.93***	-1.93***	-1.93***	-1.93***	-1.96***	-2.08***
GW state dsp		1.06***	1.08***	1.07***	1.1***	1.12***	1.14***	1.12***
GW law dsp		-0.25***	-0.25***	-0.25***	-0.26***	-0.27***	-0.26***	-0.24***
gov idea permissive	-0.26	-0.52***	-0.52***	-0.52***	-0.55***	-0.32	-0.38	-0.6***
gov idea restrictive	0.11	0.53***	0.55***	0.48***	0.46***	0.22	0.08	0.42***
restrictive law	0.54**	0.05	0.04	0.05	0.04	0.04	0.06	0.24
border		0.3***	0.29***	0.29***	0.28***	0.26**	0.26***	
homicides permissive	-0.03		0.12	0.12	0.12	0.19	0.2	0.12
homicides restrictive	0.05		0.25*	0.26*	0.24*	0.21	0.19	0.23*
backgrounds permissive	-0.05			0.04	0.04	0.02	0.03	0.05
backgrounds restrictive	-0.18			-0.27	-0.24	-0.19	-0.17	-0.22
population permissive	-0.03				0.09	0.12	0.14	0.08
population restrictive	0.19*				0.37**	0.38***	0.39***	0.34**
cit idea permissive	-0.1					-0.32	-0.35	
cit idea restrictive	0.22					0.3	0.27	
income permissive	0.12						0.12	
income restrictive	0.17						0.26	
border permissive	0.74***							0.34***
border restrictive	0.56***							0.23**
AIC	1364	1145	1146	1147	1142	1141	1141	1137

[1] *** p-value < 0.001 , ** p-value < 0.01, * p-value < 0.05Covariates effecting restrictive and permissive laws are separated, whereas structural parameters account for both law types. The edge parameter accounts for baseline density, gov idea is a measure of state government ideaology, homicides is the state per capita homicides, backgrounds is the state firearms background checks per capita, population is the raw state population, cit idea is the state citizen ideaology, income is state income per capita, border parameters correspond to the number of bordering states, that have also enacted a given law.

6 REFERENCES

Abaid, N., Macinko, J., Silver, D., Porfiri, M., 2015. The effect of geography and citizen behavior on motor vehicle deaths in the United States. PLoS One 10, e0123339.

Anderson, R.P., Jimenez, G., Bae, J.Y., Silver, D., Macinko, J., Porfiri, M., 2016. Understanding Policy Diffusion in the U.S.: An Information-Theoretical Approach to Unveil Connectivity Structures in Slowly Evolving Complex Systems. SIAM J Appl Dyn Syst 15, 1384–1409.

Andrade, E., Hoofnagle, M., Kaufman, E., Seamon, M., Pah, A., Morrison, C., 2020. Firearm laws and illegal firearm flow between US states. Journal of Trauma and Acute Care Surgery 88, 1. https://doi.org/10.1097/TA.0000000000002642

Bailey, M.A., Rom, M.C., 2004. A wider race? Interstate competition across health and welfare programs. The Journal of Politics 66, 326–347. https://doi.org/10.1111/j.1468-2508.2004.00154.x

Berry, W.D., Fording, R.C., Ringquist, E.J., Hanson, R.L., Klarner, C.E., 2010. Measuring citizen and government ideology in the u.s. States: A re-appraisal. State Politics & Policy Quarterly 10, 117–135. https://doi.org/10.1177/153244001001000201

Berry, W.D., Ringquist, E.J., Fording, R.C., Hanson, R.L., 1998. Measuring citizen and government ideology in the american states, 1960-93. American Journal of Political Science 42, 327–348.

Boehmke, F.J., 2009. Approaches to modeling the adoption and diffusion of policies with multiple components. State Politics & Policy Quarterly 9, 229–252. https://doi.org/10.1177/153244000900900205

Boehmke, F.J., Skinner, P., 2011. The determinants of state policy innovativeness 1.

Boehmke, F.J., Witmer, R., 2004. Disentangling diffusion: The effects of social learning and economic competition on state policy innovation and expansion. Political Research Quarterly 57, 39–51. https://doi.org/10.1177/106591290405700104

Butz, A.M., Fix, M.P., Mitchell, J.L., 2015. Policy learning and the diffusion of stand-your-ground laws. Politics & Policy 43, 347–377. https://doi.org/https://doi.org/10.1111/polp.12116

Carlson, J., 2020. Gun studies and the politics of evidence. Annual Review of Law and Social Science 16, 183–202. https://doi.org/10.1146/annurev-lawsocsci-020620-111332

Cherney, S., Morral, A.R., Schell, T.L., Smucker, S., 2020. Development of the RAND state firearm law database and supporting materials. RAND Corporation, Santa Monica, CA. https://doi.org/10.7249/TLA243-2

Congress, H.R.1025. - 103rd, 1994. Brady handgun violence prevention act.

Desmarais, B.A., Harden, J.J., Boehmke, F.J., 2015. Persistent policy pathways: Inferring diffusion networks in the american states. American Political Science Review 109, 392–406. https://doi.org/10.1017/S0003055415000040

Elazar, D.J., 1972. American federalism: A view from the states.

Erikson, R.S., Wright, G.C., McIver, J.P., 1993. Statehouse democracy: Public opinion and policy in the american states. Cambridge University Press, Cambridge.

Frank, O., Strauss, D., 1986. Markov graphs. Journal of the American Statistical Association 81, 832–842.

Goldenberg, A., Zheng, A.X., Fienberg, S.E., Airoldi, E.M., 2010. A survey of statistical network models. Foundations and Trends in Machine Learning 2, 129–233. https://doi.org/10.1561/2200000005

Gostin, L.O., Wiley, L.F., 2016. Public health law: Power, duty, restraint, 3rd ed. University of California Press.

Grabow, C., Macinko, J., Silver, D., Porfiri, M., 2016. Detecting causality in policy diffusion processes. Chaos 26, 083113.

Gray, V., 1973. Innovation in the states: A diffusion study. American Political Science Review 67, 1174–1185. https://doi.org/10.2307/1956539

Grinshteyn, E., Hemenway, D., 2016. Violent death rates: The US compared with other high-income OECD countries, 2010. The American Journal of Medicine 129, 266–273. https://doi.org/https://doi.org/10.1016/j.amjmed.2015.10.025

Handcock, M.S., 2003. Assessing degeneracy in statistical models of social networks.

Hunter, D.R., Goodreau, S.M., Handcock, M.S., 2008. Goodness of fit of social network models. Journal of the American Statistical Association 103, 248–258. https://doi.org/10.1198/016214507000000446

Hunter, D.R., Handcock, M.S., 2006. Inference in curved exponential family models for networks. Journal of Computational and Graphical Statistics 15, 565–583. https://doi.org/10.1198/106186006X133069

Jones, M.A., 2015. The US gun-control paradox: Gun buyer response to congressional gun-control initiatives. Journal of business & economics research 13.

Macinko, J., Silver, D., 2015. Diffusion of impaired driving laws among US states. American journal of public health 105 9, 1893–900.

Mooney, C.Z., 2021. The study of US state policy diffusion: What hath walker wrought?, Elements in american politics. Cambridge University Press. https://doi.org/10.1017/9781108956017

Morrall, A., 2018. The science of gun policy: A critical synthesis of research evidence on the effects of gun policies in the united states. Rand health quarterly 8, 5.

Pacific Institute for Research and Evaluation, n.d. Societal cost per firearm injury, united states, 2010.

Peterson, P.E., Rom, M.C., 1990. Welfare magnets: A case for a national welfare standard. Brookings Institution Press; Brookings Institution Press.

Robins, G., Pattison, P., Kalish, Y., Lusher, D., 2007. An introduction to exponential random graph (p *) models for social networks. Social Networks 29, 173–191. https://doi.org/10.1016/j.socnet.2006.08.002

Saavedra, L.A., 2000. A model of welfare competition with evidence from AFDC. Journal of Urban Economics 47, 248–279.

Shipan, C.R., Volden, C., 2014. When the smoke clears: Expertise, learning and policy diffusion. Journal of Public Policy 34, 357–387. https://doi.org/10.1017/S0143814X14000142

Smart, R., Morral, A.R., Smucker, S., Cherney, S., Schell, T.L., Peterson, S., Ahluwalia, S.C., Cefalu, M., Xenakis, L., Ramchand, R., Gresenz, C.R., 2020. The science of gun policy: A critical synthesis of research evidence on the effects of gun policies in the united states, second edition. RAND Corporation, Santa Monica, CA. https://doi.org/10.7249/RR2088-1

Snijders, T., 2002. Markov chain monte carlo estimation of exponential random graph models. Journal of Social Structure 3.

Spitzer, S.A., Staudenmayer, K.L., Tennakoon, L., Spain, D.A., Weiser, T.G., 2017. Costs and financial burden of initial hospitalizations for firearm injuries in the United States, 2006-2014. American Journal of Public Health 107, 770–774. https://doi.org/10.2105/AJPH.2017.303684

Squire, P., 2017. A squire index update. State Politics & Policy Quarterly 17, 361–371.

Takada, S., Choi, K., Natsui, S., Saadi, A., Buchbinder, L., Easterlin, M., Zimmerman, F., 2020. Network analysis of firearm movement among US states. https://doi.org/10.21203/rs.3.rs-37154/v3

Tucker, J., Stoutenborough, J., Beverlin, R., 2012. Geographic proximity in the diffusion of concealed weapons permit laws. Politics & Policy 40, 1081–1105. https://doi.org/10.1111/j.1747-1346.2012.00399.x

Volden, C., 2006. States as policy laboratories: Emulating success in the children's health insurance program. American Journal of Political Science 50, 294–312. https://doi.org/https://doi.org/10.1111/j.1540-5907.2006.00185.x

Volden, C., 2002. The politics of competitive federalism: A race to the bottom in welfare benefits? American Journal of Political Science 46, 352–363.

Walker, J.L., 1969. The diffusion of innovations among the american states. American Political Science Review 63, 880–899. https://doi.org/10.2307/1954434

Wasserstein, R.L., Lazar, N.A., 2016. The ASA statement on p-values: Context, process, and purpose. The American Statistician 70, 129–133. https://doi.org/10.1080/00031305.2016.1154108

Xu, J., Murphy, S.L., Kochanek, K.D., Arias, E., 2021. Deaths: Final data for 2019. National vital statistics reports : from the Centers for Disease Control and Prevention, National Center for Health Statistics, National Vital Statistics System 70.

Yu, J., Jennings, E.T., Butler, J.S., 2020. Lobbying, learning and policy reinvention: An examination of the american states' drunk driving laws. Journal of Public Policy 40, 259–279. https://doi.org/10.1017/S0143814X18000363

7 APPENDIX

7.1 Additional ERGM Fits

In addition to the models discussed in the main text, we considered including a number of other state level covariates. We did not find that any of these aided interpretation, but they are presented here for completeness and to enhance comparison with other studies.

We considered state legislature trifectas, where a single party controls both legislative chambers and the governorship. We considered this both as a directed variable, (0 = Democrat Trifecta, 1 = Repulican Trifecta) and as an indicator (0 = no trifecta, 1 = trifecta). Our intuition on this being that states are most likely to pass new laws when their legislatures are controlled by a single party. We included these variables in our model as the proportion of years with trifectas in our time period of interest.

We also considered the proportion of the population that were 16-25 years old and male in each state. As young males are disproportionately perpetrators and victims of violent crime, we considered that this may be important for firearms regulation.

As legislatures vary significantly from state to state in their procedures and their broad "professionalism" (Squire, 2017), we included the "Squire index." We supposed that the passing of firearms laws may be related to how each state legislature actually functions.

Table 7.1: Summaries for models with additional covariate terms, including proportion of 16-25 year old males, legislative trifectas, and the Squire index of legislative professionalism

parameter[1]	model 8	model 9	model 10	model 11	model 12	model 13
edges	-2.12***	-2.05***	-2.08***	-2.07***	-2.12***	-1.8***
gov idea permissive		-0.31		-0.23	-0.28	-0.31
gov idea restrictive		0.15		-0.14	0.03	0.21
restrictive law	0.26	0.22	0.25	0.25	0.26	-0.08
GW state dsp	1.11***	1.17***	1.14***	1.18***	1.19***	1.15***
GW law dsp	-0.23**	-0.26***	-0.25***	-0.26***	-0.24***	-0.25***
homicides permissive	0.15	0.26	0.22	0.27	0.22	0.24
homicides restrictive	0.23*	0.22	0.28*	0.27*	0.24*	0.19
backgrounds restrictive	-0.22	-0.18	-0.25	-0.23	-0.21	-0.16
population permissive	0.08	0.14	0.1	0.13	0.12	0.21
population permissive	0.08	0.14	0.1	0.13	0.12	0.21
population restrictive	0.34**	0.37***	0.35**	0.36**	0.36**	0.34*
cit idea permissive		-0.34		-0.31	-0.33	-0.32
cit idea restrictive		0.24		0.13	0.2	0.26
income permissive	-0.18	0.05	-0.22	0		
income restrictive	0.28*	0.21	0.27*	0.29		
border permissive	0.35***	0.29**	0.32**	0.29**	0.32***	0.31***
border restrictive	0.26**	0.21*	0.23**	0.19*	0.21*	0.22*
trifecta permissive	0.46**		0.55**	0.58*		
trifecta restrictive	-0.64***		-0.48*	-0.15		
trifecta indicator permissive					0.43	
trifecta indicator restrictive					-0.2	
young males permissive		0.23	0.35*	0.24		
young males restrictive		0.15	0.19	0.18		
squire index permissive						0.19
squire index restrictive						-1.42
AIC	1132	1135	1128	1136	1138	1139

[1]*** p-value < 0.001 , ** p-value < 0.01, * p-value < 0.05Covariates effecting restrictive and permissive laws are separated, whereas structural parameters account for both law types. The edge parameter accounts for baseline density, gov idea is a measure of state government ideaology, homicides is the state per capita homicides, backgrounds is the state firearms background checks per capita, population is the raw state population, cit idea is the state citizen ideaology, income is state income per capita, border parameters correspond to the number of bordering states, that have also enacted a given law. Trifecta are coded as 1 = Republican trifecta, 0 = Democratic trifecta, trifecta indicator is coded as 1 = any trifecta, 0 = no trifecata, the covariate for the network is then the mean of these indicators over all years in the data. Young males is the proportion of the populations that are 16-24 year old males. Squire index is a measure of legislative professionalism