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Understanding Policy Diffusion in the U.S.: An Information-Theoretical Approach to Unveil Connectivity Structures in Slowly Evolving Complex Systems

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Abstract

Detecting and explaining the relationships among interacting components has long been a focal point of dynamical systems research. In this paper, we extend these types of data-driven analyses to the realm of public policy, whereby individual legislative entities interact to produce changes in their legal and political environments. We focus on the U.S. public health policy landscape, whose complexity determines our capacity as a society to effectively tackle pressing health issues. It has long been thought that some U.S. states innovate and enact new policies, while others mimic successful or competing states. However, the extent to which states learn from others, and the state characteristics that lead two states to influence one another, are not fully understood. Here, we propose a model-free, information-theoretical method to measure the existence and direction of influence of one state's policy or legal activity on others. Specifically, we tailor a popular notion of causality to handle the slow time-scale of policy adoption dynamics and unravel relationships among states from their recent law enactment histories. The method is validated using surrogate data generated from a new stochastic model of policy activity. Through the analysis of real data in alcohol, driving safety, and impaired driving policy, we provide evidence for the role of geography, political ideology, risk factors, and demographic and economic indicators on a state's tendency to learn from others when shaping its approach to public health regulation. Our method offers a new model-free approach to uncover interactions and establish cause-and-effect in slowly-evolving complex dynamical systems.

Keywords

causality; complex dynamical systems; health policy; information theory; networks

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1. Introduction

The U.S. Institute of Medicine has called public policies among the most powerful tools to improve population health [1]. But widespread adoption of such policies is complicated by the U.S. federal system, in which decision-making on a variety of areas affecting people's health and livelihoods remains the responsibility of state or local government. Of key interest is how to promote the diffusion of effective policies and programs across these decentralized government units. There are currently few lessons learned to help guide federal or state decision-makers in meeting this challenge [2], and even less is known about the types of policies that different legislative bodies may be more likely to adopt or repeal [3].

In an effort to understand state-to-state policy variation, recent work has focused on identifying internal and external factors that characterize the likelihood that a given state will adopt a new policy [4]. A common belief is that some states consistently act as innovators of new policy [4–6], while other states follow in their footsteps, enacting legislation that is designed to emulate successful policies [7] or reduce potential economic competition [8]. Thus, the evolution of the public policy landscape can be described using the language of complex networks [9] and dynamical systems, whereby individual states form a set of interacting elements, possibly leading to the propagation of individual laws. Toward explaining the dynamics of these processes, several approaches have sought to isolate the determinants of whether a given state will adopt a new law. In the event history analysis approach [10], internal and cross-state pressures are included in models to predict state adoption of a specific law between any given state pairs (dyads). Further work using this approach has identified state factors associated with policy diffusion in the regulatory domains of tobacco [11], health insurance [7], schools [12], and others [13, 14].

We propose that the field of dynamical systems can greatly contribute to the analysis of policy diffusion. This paper builds on a series of complex dynamical systems methods that detect connectivity, causality, and information flow between variables in time series data [15–28]. The attractiveness of these methods has been demonstrated in the reconstruction of climate networks [29, 30], the inference of functional connectivity in neuroscience and finance [31–33], and in the quantification of interactions among animals [34–39]. From these methods, a modern approach to reconstructing influences and their covariates from recorded data has blossomed, but typically, it requires a vast amount of rich and highly-variable data. Reconstruction of networks with limited data often depends on the solution of an optimization problem that fits observed data to a particular model [40, 41]. Changes in the public policy landscape, however, are relatively slow and are the consequence of a variety of difficult-to-model factors, thus requiring advancements to assess influence from arbitrarily large periods of inactivity.

Here, we investigate a series of competing hypotheses about factors that may act as determinants of one state's tendency to adopt new public health laws based on changes in the laws of another. Specifically, we offer a new quantitative method to examine the relationship between a state's characteristics and the amount of information, defined in terms of entropy [42], that is transferred between pairs of states. Considering interactions in a model-free, information-theoretical framework permits exploratory investigations without requiring the *a priori* definition of the types of interactions among states that signify policy emulation. We illustrate its application to state laws within the domains of alcohol, driving safety, and impaired driving regulation.

We choose to examine policies regarding alcohol and traffic safety because motor vehicle collisions (MVCs) remain one of the leading causes of preventable death in the United States, with over 33,000 deaths in 2012 [43], and are estimated to incur a total economic cost of nearly $100 billion [44]. Alcohol consumption represents a significant risk factor for disease and injury [45] and has been proposed as a primary contributor to fatal MVCs, accounting for 31 % of MVC fatalities in 2012 [43]. Significant variation exists between these figures by state — MVC death rate varies fourfold by state [43], and the percentage of these fatalities due to alcohol currently ranges from 16% in Utah to 44% in Montana [46]. Responsibility for establishing alcohol and traffic laws primarily lies with individual states. However, despite evidence of the effectiveness of specific policies in lowering mortality and morbidity [47, 48], the total number of adopted and retained laws vary considerably among states. In this study, we focus on law enactments and changes to states' beer tax rates, dramshop liability laws, host liability laws, Sunday sales bans, and beer keg registration (for alcohol regulation); distracted driving laws, driver and occupant protection laws, graduated driver's license (GDL) programs, and child restraints (for driving regulations); and open container laws, penalties for driving under the influence (DUI), and zero tolerance laws (for impaired driving regulation).

Based on these laws, we compute the amount and direction of influence that one state has on another by examining if the union of historical law activity in two states better enables the prediction of future law activity in one of them. This prediction is defined in terms of an entropy reduction, and we name the new measure of causality "union transfer entropy." In order to validate the method, we also establish a new stochastic model to simulate law activity that captures many salient features of the evolution of a state's changing legal and political environment. We investigate how policy diffusion relates to variation in the states' health outcomes, their geographic contiguity, and other explanatory variables, which have all been proposed as determinants of states' law enactment [47, 48]. Thus, in a novel information-theoretical framework, we systematically dissect the contribution of these state attributes, laying the foundation for causal analysis in public health policy.

2. Datasets

Law enactment data originates from the public use State Health Policy Research Dataset (SHePRD) [49] and includes regulations, taxes, and other enforcement mechanisms from the domains of alcohol regulation, general driving regulations, and impaired driving regulations, across all $N = 50$ states, and for the years 1980 – 2010. The laws were selected based on published evidence of their impact on reducing morbidity and mortality. The laws we use can be found in Appendix A and Tables Al, A2, and A3 for alcohol, general driving, and impaired driving regulations, respectively. In these tables, we also provide the number of states that have enacted legislation relating to the law between 1980 – 2010. For each law, and within the horizon of January 1, 1980 until December 31, 2010, legal databases were searched to identify the specific day a law change became effective, including law implementation (a law first comes into existence with the specified effective date), amendment (a material change in an existing law is enacted on the specified date), or repeal (an existing law is reversed, effective on the specified date).

These data are assembled by day into a time series of length $T = 11323$ (i.e., 31 years) that describes, for each state and for each law, whether or not any activity occurred on a given day. More formally, for each state $i = 1, \ldots, N$, for each considered law k in that state (out of K total laws), $k = 1, \ldots, K$, and for each day $t = 1, \ldots, T$, a binary variable $x_{ik}(t)$ takes value 1 if the law k in state i was implemented, repealed, or experienced material change on day t, and it is 0 otherwise. For instance, if the beer tax rate in New York increased from 11 % to 14 % on a particular day t, the variable corresponding to New York and "beer tax rate" should be 1 at day t.

In addition to the dates of law activity for each state, various features of each state are identified in order to build pairwise measures of dissimilarity between two states i and j, where i and j each range from one to 50. The dissimilarities considered in this work are presented in Table 1 and comprise measures that characterize geographic or cultural dissimilarity (in rows 1–3), and differences in health outcomes (rows 4–5), demographics (rows 6–8), and economic factors (rows 9–10). We denote symmetric measures of dissimilarity by $\upsilon(i, j)$ and directed measures as $\upsilon(j \rightarrow i)$, with subscripts for each of the measures listed in Table 1.

3. Union transfer entropy for inferring causality among states

To estimate the magnitude and direction of influences among states from either real or simulated law activity, a data-driven approach is developed to quantify the amount of information flow between two states. For this purpose, we consider a type of conditional mutual information [22] related to the union of law activity over a historical period. In this section, we define union transfer entropy, explain a method for its calculation, and explain how we use it to quantify interactions among states from their legal histories. While the exposition is tailored toward unraveling influences among states, we present our approach in rather general terms to ease its application to other slowly-evolving systems.

We start with a dynamical sy stem composed of N distinct units (in this case, $N = 50$ states), each with $k = 1, \ldots, K$ binary-valued time series $x_{ik}(t)$ where $t = 1, \ldots, T$ is the discrete time variable. For our public health problem, $x_{ik}(t)$ is the value of the k-th law in state i on day t. We further allow for the case where the K time series of each unit i can be assembled into groups $X_{i\ell}(t) = \{x_{ik}(t)\}_{k \in \text{group } \ell}$ such that $\cup_\ell X_{i\ell}(t)$ forms the set of available time series data, the index ℓ spans the set of groups, and group ℓ includes the values of k associated with the ℓ-th group. In our study, such a representation is useful to group the K laws into the law domains of alcohol, safe driving, and impaired driving ($\ell = 1$, 2, and 3), since inter-state influence likely varies across these domains. We then analyze the inter-state influences within these domains as if they were independent problems.

We seek to establish a measure, so called union transfer entropy and denoted $I_t(j \rightarrow i)$, where $i, j = 1, \ldots, N$ and $j \neq i$, quantifying the influence that $X_j(t)$ has on $X_i(t)$, in order to elucidate the contribution of state attributes on law enactment. This calculation examines whether or not the union of all law activity in one state over a historical horizon enables a better prediction of the law activity in another state.

3.1. Model-free measurement of inter-state influence from law activity

The procedure for measuring the directed influence from one state to another is divided into two parts. First, the law activity for a pair of states is used to form an empirical probabilistic representation of whether or not law activity tends to occur in one state on a particular day with respect to any recent law activity in both states. These probabilities are then incorporated into the calculation of a type of conditional mutual information between law processes of two states, which quantifies the information flow.

3.1.1. Calculation of empirical probabilities—Given two states i and j and a law variable k, a joint distribution on a triplet of law activity indicators over the horizon $t = 1, \ldots, T$ is formed based on a sliding window of length $\bar{T}$ (see Figure 1) that includes

1. Whether or not any activity in law k occurred in state i on day t, which is given by the binary random variable $x_{ik}(t)$;
2. Whether or not any activity in law k occurred in state i in the previous $\bar{T}$ days following day t, which is denoted as $y_{\mathrm{ik}}(t)=\bigcup_{r=\max\{t-\overline{T},1\}}^{t-1} x_{\mathrm{ik}}(r)$; and
3. The same as (2), but for state j, which is denoted as $y_{jk}(t)$.

This joint distribution $P(x_{ik}(t), y_{ik}(t), y_{jk}(t)) \in [0, 1]$ is estimated using the empirical frequencies of each possible binary outcome observed in the data as

$$P(x_{\mathrm{ik}}(t), y_{\mathrm{ik}}(t), y_{\mathrm{jk}}(t))=\frac{1}{T}\sum_{t=1}^{T} x_{\mathrm{ik}}(t)y_{\mathrm{ik}}(t)y_{\mathrm{jk}}(t). \quad (3.1)$$

To make the method less sensitive to noise, we combine the empirical distributions for all laws under a given group (law domains of alcohol, safe driving, or impaired driving) into joint distributions $P(X_i(t), Y_i(t), Y_j(t))$, from which the conditional distributions $P(X_i(t)| Y_j(t))$ and $P(Y_i(t)| Y_i(t), Y_j(t)$ are calculated through appropriate marginalizations and use of conditional probability formulae [58].

Considering the union $y_{ik}(t)$ of law activity over the previous $\bar{T}$ days allows for the method to account for processes which only a small number of events (where $x_{ik} = 1$) occur in a given window. On the other hand, if many events over a historical period are reduced to a value $y_{ik}(t) = 1$ by taking the union of events over such a window, valuable information that may help determine causality can be lost. As such, this method is expected to be more appropriate for slowly-varying processes.

3.1.2. Calculation of conditional mutual information—The new measure of causality we use to identify information flow from state i to state j for group ℓ, denoted $I_\ell(j \to i)$, is defined as

$$I_\ell(j \to i) = H(X_{i\ell}(t)|Y_{i\ell}(t)) - H(X_{i\ell}(t)|Y_{i\ell}(t), Y_{j\ell}(t)). \quad (3.2)$$

The information flow is the difference between two conditional entropies [42] $H(X_{i\ell}(t)|Y_{i\ell}(t))$ and $H(X_{i\ell}(t)|Y_{i\ell}(t), Y_{j\ell}(t))$, which can be computed as

$$H(X_{i\ell}(t)|Y_{i\ell}(t)) = -\sum_{X_{i\ell}(t), Y_{i\ell}(t)} P(X_{i\ell}(t)|Y_{i\ell}(t)) \log\left[P(X_{i\ell}(t)|Y_{i\ell}(t))\right] \quad (3.3)$$

$$H(X_{i\ell}(t)|Y_{i\ell}(t), Y_{j\ell}(t)) = -\sum_{X_{i\ell}(t), Y_{i\ell}(t), Y_{j\ell}(t)} P(X_{i\ell}(t)|Y_{i\ell}(t), Y_{j\ell}(t)) \log\left[P(X_{i\ell}(t)|Y_{i\ell}(t), Y_{j\ell}(t))\right], \quad (3.4)$$

where we choose the logarithm to be natural. The first term can be interpreted as the uncertainty in the prediction of the activity in the group ℓ in state i, given the union of all activity in group ℓ over a historical period in that state. The second term is the uncertainty in the same quantity, but in the case that the union of historical activity in group ℓ in another state is known. Thus, the interpretation of $I_\ell(j \to i)$ is as follows. If the uncertainty of the prediction of the process $X_{i\ell}(t)$, given the union of all recent law activity in state i, is reduced by additionally conditioning on the union of all law activity in state j, then state j is said to have influence over state i. Hence, this measure is a type of "predictive causality."

The non-negative quantity $I_\ell(j \to i)$ is directed (asymmetric), meaning that, in general, $I_\ell(j \to i) \neq I_\ell(i \to j)$. A larger value of $I_\ell(j \to i)$ implies that knowledge of historical activity of group ℓ in state j improves the prediction of the activity in the group ℓ in state i. A smaller value of $I_\ell(j \to i)$ indicates the activity of group ℓ in state i is essentially independent of that in state j. While intertwined causal relationships among multiple states cannot be dismissed, our approach is tailored to pairwise interactions, whose detection can be afforded using the available data. Future work will seek to examine the relationship between data density and reconstructible features of the network topology. Rather than empirical evidence, this analysis should use comprehensive synthetic datasets, expanding on the model of law activity presented in what follows.

The information flow from state ℓ to state i in a group ℓ is the average of the information flows for the window sizes $\bar{T} = 2$, 3, 4, and 5 years. These horizons are based on an assumption of the amount of time required for one state's law activity to influence that of another. Since the events in one time horizon also include the events in a shorter time horizon (e.g., $I_\ell(j \to i)$ for $\bar{T} = 2 \times 365$ is based on events also found in $I_\ell(j \to i)$ for $\bar{T} = 3 \times$

365), then this procedure places greater weight on short time delays between the activity in one state that may cause activity in another.

3.2. Comparison of inter-state influence (Equation 3.2) and transfer entropy

The new measure of information flow in Equation (3.2) is a type of conditional mutual information and shares many similarities with transfer entropy [21, 22, 25, 31, 32, 34, 35, 59, 60], a celebrated measure of information flow between two processes. To ease comparison of transfer entropy and union transfer entropy, we consider just one group $\ell = 1$ consisting of a single law $k = 1$, so that $X_{i1}(t) = \{x_{i1}(t)\}$, and we correspondingly simplify the notation of union transfer entropy in (3.2) as

$$I(j \to i)=H(x_i(t)|y_i(t)) - H(x_i(t)|y_i(t), y_j(t)). \quad (3.5)$$

Computation of the (one-step) transfer entropy from state j to state i, would entail the computation of

$$\mathrm{TE}(j \to i)=H(x_i(t)|x_i(t-1)) - H(x_i(t)|x_i(t-1), x_j(t-1)). \quad (3.6)$$

In order to include interactions with earlier law enactment events, transfer entropy can be expanded to include a history $x_i^{(r)}(t)=[x_i(t-r+1), \dots, x_i(t-1)]$ of length r of the law enactments in state i, and the history $x_j^{(r)}(t)$ in state j, which is defined similarly, as

$$\mathrm{TE}(j \to i)=H\left(x_i(t)|x_i^{(r)}(t)\right) - H\left(x_i(t)|x_i^{(r)}(t), x_j^{(r)}(t)\right). \quad (3.7)$$

These conditional entropies, in turn, would require the estimation of the conditional distributions $P\left(x_i(t)\middle|x_i^{(r)}(t)\right)$ and $P\left(x_i(t)\middle|x_i^{(r)}(t), x_j^{(r)}(t)\right)$ from the law enactment data using the empirical frequencies of each observed joint occurrence of $\left(x_i(t), x_i^{(r)}(t), x_j^{(r)}(t)\right)$ as in (3.1). Accurate estimation of the empirical frequencies of $\left(x_i(t), x_i^{(r)}(t), x_j^{(r)}(t)\right)$ for large r requires observation of long histories of time series $x_i(t)$ and $x_j(t)$, and accurate estimation of the conditional entropies in (3.7) requires even more data, as entropy estimators can be notoriously biased [61]. If the history length r were reduced back to $r = 1$, so that the transfer entropy could be estimated using (3.6), then almost all observed triplets $(x_i(t), x_i(t-1), x_j(t-1))$ would be empty, as law enactments are rare events. We also find that downsampling a law enactment time series is too restrictive; transfer entropy computation using a year as a time step is not adequate.

Comparing (3.7) with (3.5), we remark that the influence between states considered in this work seeks to capture large histories of infrequently-changing state law enactment data, while still remaining computationally feasible. In light of the low rate of law activity over the considered 31 year period, state influences are constructed on the basis of the union of historical law activity over a specified horizon.

3.3. Model of law activity for methodology validation

In order to validate the proposed methodology to infer directions of influence among states from $x_{ik}(t)$, we propose a stochastic process to generate surrogate data based on a known network of influence among states. We describe in this section the formulation of the process and explain its parameters; the procedure to estimate these parameters from real data is illustrated in Appendix B.

We define a graph $G = (V, E)$ comprised of a set of vertices V, one for each state, and a set of edges E such that if state j influences state i, then an edge from j to i is in E. The nodes j that can influence node i, that is, the nodes j for which an edge exists from j to i, is denoted as the set $\mathcal{N}_i$. For expository purposes, we choose the network topology to be 1-out [62] regular, or ring-like, whereby state 1 influences state 2, state 2 influences state 3, and so on. In other words, $i + 1 \in \mathcal{N}_i$ for $i = 1, \ldots, 9$, and $\mathcal{N}_{10} = \{1\}$.

Next, a discrete-time stochastic process based on the graph G determines the law change events. On any given day, either no law activity occurs, or there is activity independent of other states, or the outcome (activity / no activity) is determined by that state's connected neighbors, as defined by G. More formally, for each state i, $i = 1, \ldots, N$, for each considered law k in that state, $k = 1, \ldots, K$, and for each day t, $t = 1, \ldots, T$, a binary variable $x_{ik}(t)$ takes value 1 if the law k in state i was implemented, repealed, or experienced material change on day t, and it is 0 otherwise. A model with the following form encapsulates the law activity for the state i:

$$x_{\mathrm{ik}}(t)=\nu_{\mathrm{ik}}(t)\left[\eta_{\mathrm{ik}}(t)+(1-\eta_{\mathrm{ik}}(t))\left(1-\prod_{r=\tau_{\mathrm{ik}}(t)}^{t-1}\prod_{j\in\mathcal{N}_i}[1-x_{\mathrm{jk}}(r)]\right)\right]. \quad (3.8)$$

Here, $\nu_{ik}(t)$ and $\eta_{ik}(t)$ are independent and identically distributed (i.i.d.) Bernoulli random variables with parameters α and β, respectively, and

$$\tau_{\mathrm{ik}}(t)=\max\{\ell<t:x_{\mathrm{ik}}(\ell)=1\} \quad (3.9)$$

is the most recent day before day t that state i experienced activity in law k.

Equation (3.8) implies that activity in law k is allowed to occur on day t only if $\nu_{ik} = 1$, which happens with probability α. Given that law activity is capable of occurring on day t, i.e., $\nu_{ik}(t) = 1$, then with probability β, that activity is independent of any neighbors ($\eta_{ik}(t) = 1$), while with probability $1 - \beta$, $x_{ik}(t)$ is determined by the law activity history of that state's neighbors $\mathcal{N}_i$. In this case, $x_{ik}(t)$ takes value 1 if any neighbor $j \in \mathcal{N}_i$ has had activity in law k since state i has last displayed activity in law k. In other words, β describes the tendency for a state to act independently of others who might otherwise influence it. For simplicity, we assume that the values of a and β are constant and shared by all states.

We choose the values of these parameters through an expectation maximization procedure [63] with real law activity data, as described in Appendix B. Note that in this approach, law activity is either random, or it is influenced by another state's activity in the same category k (e.g., "NY beer tax rate" might influence "NJ beer tax rate"). Distinct laws types (e.g., "beer tax rate" and "Sunday ban") are assumed to evolve independently across states. This assumption can be relaxed in favor of more complex forms of interactions, weighting the influence from multiples states' law activities. Such an extension will be the subject of future work. An example of the possible routes to the outcomes in the present work is depicted in Figure 2. Equation (3.8) is simulated for $N = 10$ states and $K = 38$ laws with initial condition $x_{ik}(1) = 1$ for all i and k. After discarding the first 10 years of simulated data, 31 years ($T = 11323$) of law activity are collected.

3.4. Characterization of the relationship between inter-state dissimilarities and influences

A central element of our analysis is to understand the determining factors for inter-state influences, a more focused and less challenging task than fully reconstructing the topology of the interactions among states, which will be the objective of future studies. These determining factors are detected by comparing the influences estimated from the law data, using our new theoretical construct of union transfer entropy, to the dissimilarities between states (geographical and cultural dissimilarities, and differences in health outcomes, demographics, and economic factors; see Table 1). To perform a rigorous statistical analysis, we focus on a set of key hypotheses that can be verified through pairwise comparison of data partitioned in two clusters. For example, to ascertain if ideology is a key factor in determining the inter-state influence, we would partition state pairs on the basis of their relative degree of conservativeness or liberality, and then compare the overall influence of more conservative states on liberal states to the overall influence of more liberal states on conservative states.

More specifically, for real law activity, and for each of the directed dissimilarity measures $\upsilon(j \rightarrow i)$ in Table 1, we assign directed pairs of states $(j \rightarrow i)$ to one of two clusters depending on the sign of the dissimilarity measure. For instance, if $\upsilon_I(j \rightarrow i) < 0$, then state j is on average more conservative than state i, and the directed pair $(j \rightarrow i)$ is placed in one cluster. Those states with $\upsilon_I(j \rightarrow i) > 0$ are placed in a second cluster. The median of the total influence of state j to state i for those state pairs in one cluster is compared against the median of the influence for those state pairs in the other with a Wilcoxon rank-sum test [64]. The threshold $p < 0.05$ is used for significance.

For the case of geographical distance $\upsilon_G(i, j)$, which is symmetric, those state pairs that share a border are placed in one cluster, and those state pairs that are not adjacent are placed in the other. Similarly, the red/blue distance $\upsilon_{R/B}(i, j)$ is a binary variable and is clustered by this value. To compare influence $I_{\ell}(j \rightarrow i)$, which is directed, to $\upsilon_G(i, j)$ and $\upsilon_{R/B}(i, j)$, which are symmetric, the union transfer entropy between two states is also symmetrized as $I_{\ell}(i, j) = I_{\ell}(j \rightarrow i) + I_{\ell}(i \rightarrow j)$ to yield the total information flow $I_{\ell}(i, j)$ between two states. The median of the total information flow for those state pairs in one cluster is compared against the median of the total information flow for those state pairs in the other with a Wilcoxon rank-sum test [64], with the threshold $p < 0.05$ for significance.

In the case of simulated law activity, where the underlying network is known, the influences $I_\ell(j \to i)$ for those state pairs where j influences i are compared to those state pairs in which j does not influence i using a rank-sum test, with the threshold $p < 0.05$ for significance.

We also examine pairwise correlations between each of the dissimilarity measures across 50 states to test for possible relationships between these measures. We compute the Pearson correlation coefficient [65] R for various each of the asymmetric dissimilarity measures in Table 1 (that is, all but $\upsilon_G(i, j)$ and $\upsilon_{R/B}(i, j)$) and test its statistical significance using an R-to-t conversion with subsequent t-test [65]. All analysis is performed in Matlab.

4. Results

4.1. Surrogate data shares similarities with real data and enables identification of causal relationships

Figure 3(a) depicts the dates in which the state excise tax rate on packaged beer by volume experienced any activity (enactment, change, or repeal) over the years 1980–2010 for 10 states. Alongside these real data, in Figure 3(b) we generate surrogate activity for 10 states for the years 1980–2010 using the developed stochastic process, where a rule for state-to-state influences is chosen such that state 1 can influence state 2, state 2 can influence state 3, and so on, where the final state 10 can influence state 1. The underlying influences (state 1 influences 2, and so on) that resulted in policy adoption in the simulated data are highlighted in with pairs of hatch marks. Comparing Figure 3(a) and Figure 3(b), we note a similar sparse pattern, illustrating quantitative and qualitative similarities between law enactment activities and surrogate data from the stochastic model.

4.2. Union transfer entropy reveals the influences underlying a surrogate dataset

Figure 3(c)–(d) shows the computed union transfer entropy $I_\ell(j \to i)$ for the ten states or nodes in Figure 3(a)–(b) based on real or simulated data. The union transfer entropy $I_\ell(j \to i)$ from state j to state i, where $i \neq j = 1, \dots, 50$, and group ℓ (either alcohol regulations, driving regulations, or impaired driving regulations) is positive if the ability to predict the law activity of state i is improved by knowledge of the historical law activity of state j. Like the true influences that determine the simulated law activity, $I_\ell(j \to i)$ is a directed quantity and is designed to be larger if state j influences state i in the true topology of interaction that underlies the simulated law activity. Figure 3(c)–(d) shows the computed union transfer entropy $I_\ell(j \to i)$ for the ten states or nodes in Figures 3(a)–(b) based on real or simulated data. Comparing the estimates $I_\ell(j \to i)$ from simulated data, a Wilcoxon rank sum test [64] reveals that state pairs $(j \to i)$ that also exist in the surrogate model yield higher union transfer entropy estimates $I_\ell(j \to i)$ ($z = 3.73$, $p < 0.05$). To examine the effect of the duration of the observed activity on this comparison, we also simulate law activity in 10 states for the years 1920–2010. State pairs that exist in the ring-like topology are found to consistently display higher union transfer entropy ($z = 3.02$, $p < 0.01$), see Figure 4.

4.3. Union transfer entropy measured from real law activity relates to state dissimilarity

The union transfer entropy from state j to state i is computed for the law domains (groups) of alcohol, safe driving, and impaired driving, and for all 50 states. We group pairs of states based on measures of dissimilarity between them that capture competing hypotheses on the mechanisms behind law activity. For instance, we group together state pairs in which state j is, on average, more ideologically conservative than state i; the union transfer entropy estimates $I_t(j \to i)$ of this group are compared against those of state pairs where j is, on average, more liberal than state i. The complete list of the 10 measures of dissimilarity we consider and the methodology utilized for clustering state pairs based on these measures, is found in Table 1. By focusing on such fundamental relationships between state pairs, instead of only the estimated value of the union transfer entropy, we seek to reduce the potential for spurious relations [67] among states, which may influence our ability to discern key factors in policy diffusion.

Figure 5 shows that union transfer entropy in the alcohol regulation domain is greater for two states that share a border (Wilcoxon rank sum test; $z = 2.05$, $p < 0.05$). Union transfer entropy in the alcohol regulation domain is larger in the direction from state j towards state i if state i is, on average, more liberal than state j ($z = -2.75$, $p < 0.01$); the opposite is true for the driving domain ($z = 6.086$, $p < 0.0001$) and the impaired driving domain ($z = 6.99$, $p < 0.0001$). Impaired driving laws show a slight tendency to cross the ideological divide ($z = -2.11$, $p < 0.05$). However, for alcohol and driving, we observe no significant difference between the union transfer entropy estimates for two states that share the same political ideology and those states whose ideologies differ ($z = -0.15$, $p = 0.88$ alcohol; $z = 1.09$, $p = 0.27$ driving). Note that these estimates are blind to the content of the laws and are computed without regard for the possibility that the enacted laws embody a particular ideology.

Figure 6 illustrates that in terms of variation in health outcomes, alcohol, driving, and impaired driving policies all yield higher union transfer entropy in the direction of states with higher deaths due to motor vehicle collisions per capita than in the opposite direction ($z = -2.02$, $p < 0.05$ alcohol; $z = -5.37$, $p < 0.0001$ driving; $z = -3.12$, $p < 0.001$ impaired driving). Moreover, alcohol domain union transfer entropy is higher in directions towards states with less ethanol consumption per capita ($z = 3.86$, $p < 0.0001$).

Alcohol regulations also show greater influence on states with greater populations ($z = -2.44$, $p < 0.01$) and populations densities ($z = -2.73$, $p < 0.001$); the opposite is true for driving regulations ($z = 3.31$, $p < 0.001$; $z = 8.14$, $p < 0.0001$), see Figure 7. Union transfer entropy in driving regulations is also larger in directions towards states with higher numbers of motor vehicle registrations per capita ($z = -6.06$, $p < 0.0001$). These directions for driving regulation flow are matched by those of impaired driving, which also flow towards less population density ($z = 4.43$, $p < 0.0001$) and more MV registrations ($z = -1.97$, $p < 0.05$).

Based on economic indicators, we find that union transfer entropy is larger in the direction towards states with higher gross domestic product (GDP) for alcohol ($z = -2.11$, $p < 0.05$), and away from high GDP for driving regulation ($z = 3.83$, $p < 0.0001$) and impaired driving regulations ($z = 1.78$, $p < 0.05$), see Figure 8. Finally, both alcohol regulation influence and impaired driving influence tend to flow towards states with a higher percentage of people below the federal poverty line ($z = -3.99$, $p < 0.0001$ alcohol; $z = -2.62$, $p < 0.01$ impaired driving).

To examine confounding factors in the revealed relationships between union transfer entropy estimates and the selected measures of dissimilarity, we also explore correlations between each of them. The Pearson correlation coefficient between each of the dissimilarity measures for all pairs of states is found in Table 2. Note that these are not direct correlations between state factors, such as population and GDP, but rather the correlation in differences in these factors across the pairs of states. For instance, this table shows that if one state has a higher GDP than another, then that state is (unsurprisingly) also likely to have a higher population ($R = 0.99$).

5. Discussion

In this study, we present a model-free method to uncover the existence and direction of influences among states in their regulation of alcohol, driving safety, and impaired driving, based solely on the times at which their legislative bodies enact specific laws. This approach offers a new method for the analysis of complex dynamical systems, tailored for slow time-scale processes. Using this method, we examine a series of competing hypotheses that have arisen in earlier works to explain the mechanisms behind the diffusion of policy. However, in contrast with these previous studies, our approach does not assume a functional relationship between the timing or number of law adoption events and these mechanisms. Instead, we concentrate on measuring the influence of one law state's enactment process on another in terms of the information flow between the states, laying the foundation for causal analysis in the realm of state public health policy adoption. Given the size of the dataset, we focus on general state-level behavioral rules constructed on the basis of state characteristics and inter-state variation, rather than independent evolution of state laws. The latter would require a considerably larger dataset, representing a longer history.

Through comparisons of union transfer entropy estimates with corresponding differences in state attributes, we confirm that internal state characteristics play a significant role in the adoption of alcohol, safe driving, and impaired driving policies, as posited in [10]. In addition, the alignment of the differences in attributes between two states with the direction of influence between them often favors one of two competing hypotheses. For example, results suggest that alcohol regulations in two adjacent states are more likely to be influenced by one another. This is supported by a number of previous studies that relate a state's adoption of a novel policy to the policies of its neighbors [10, 11, 68], which is, in turn, thought to be caused by a combination of learning [5], economic pressures driven by contiguity [8], and the similarity of problems faced by nearby states.

However, we find that geographic adjacency is not the only factor driving the influences behind the policy adoption process. The fact that all three considered regulatory domains (alcohol, safe driving, and impaired driving) reflect influences towards states with a higher MVC death rate suggests that health outcomes may form the backbone behind the diffusion of these regulations. This finding may be due to a mimetic tendency for one state to emulate the policies of other states that were proven successful in modulating specific health concerns, a process that is commonly discussed as a driver of policy diffusion [4]. Alternatively, it may be hypothesized that states with a higher MVC death rate are more receptive to laws that might address the problem, irrespective of their source.

Regarding variation in a state's political ideology, our findings suggest that liberal states are more likely to be influenced by conservative states on alcohol regulation than *vice versa*. However, we observe no greater influence between two states of opposite ideology than between two states that share the same ideology. This is in contrast to some previous works, which suggest that policy may diffuse through pathway s of shared beliefs and identities [69, 70]. For alcohol policy, at least, our results posit that states may be willing to reach across the ideological divide for policy solutions or even emulate a neighbor on the opposite side of the political spectrum. It may also be proposed that liberal states are more receptive to alcohol regulation, and therefore more susceptible to influence from other states, including those that do not share their political orientation.

An opposite effect is found in driving and impaired driving regulations, where politically conservative states are more likely to receive influence from liberal states than the other way around. This finding may potentially be ascribed to a willingness in liberal states to venture into driving regulation, while conservative states trail. However, conservative states bear on average a higher MVC death rate [71], and thus it can be hypothesized that a desire to reduce such figures may prompt policy emulation. Other state descriptors that are shown to have a bearing on the direction of influence may similarly be attributed to a higher rate of death due to MVCs. Considering non-negligible correlations between the measures of dissimilarity used in this study, a higher MVC death rate in one state is also associated with a higher conservativeness, lower population, lower population density, lower GDP, and a larger number of individuals below the poverty line. Indeed, a number of these factors are associated with a greater flow of influence into a state. For example, driving regulation influence tends in the direction of a state with a lower GDP, lower population, less population density, and more MV registrations per capita. While the cause of such correlations may be speculated about (for instance, places with lower population density have households with more motor vehicles largely because they more are dependent on them), they also hinder the ability to discern the relative role of the individual factors.

In all six measures of state dissimilarity in which a union transfer entropy estimate was significantly larger in one direction, that direction was reflected both in safe driving domains and impaired driving domains. While impaired driving may be interpreted as a middle ground between alcohol regulation and safe driving regulation, our results suggest that states learn impaired driving regulation from others in the same way that they learn safe driving regulation. On the other hand, factors underlying the directions of influence are shared between alcohol and impaired driving regulations in only two out of five cases (deaths per VMT and % poor).

Overall, this study demonstrates the feasibility of testing policy diffusion hypotheses using a model-free notion of state interactions that relies only on law activity data. In applying this method to analyze states' political landscapes, any potential confounding variables, such as global media outlets or political movements at the federal level, are likely to affect multiple states at once and will thus be filtered by the proposed scheme. Moreover, different from some recent techniques to measure causality from time series data [22], our method can naturally handle law activity occurring over long historical periods with relatively little regulatory activity, and is therefore tailored to the slow rate of change of state-wide policy.

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We anticipate that this method may find use in the analysis of complex systems beyond public policy, including the causal analysis of rare or extreme events in finance [72], ecology [73], and international relations [74].

Our findings naturally give rise to additional questions about the dynamics of the law adoption, be it learning, emulation, or even competition [7, 8], and on the role of more complex relationships [75] among states. However, in order to fully capture the influences among states using these methods, a vast catalog of daily law activity is needed. This suggests that further study of causal relationships and variation in policy adoption across legislative bodies could benefit from additional, high-resolution data comprising daily law activity. Moreover, it hints at future challenges in properly dissecting local, state, federal, and even international [76, 77] policy trends to better understand the phenomena that control the dynamics of these processes. Further insight into this complex landscape could be obtained by including steps supervised by human experts in our data-driven analysis, toward quantifying the significance of individual law activities and, possibly, determine hierarchical relationships among them.

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Appendix A

Laws considered for analysis

Tables Al, A2, and A3 list the laws considered for analysis along with their sources. While the authors largely relied on secondary sources summarizing the laws, the law data were often supplemented by original legal research to cover any missing historical versions or specific elements of the laws. Using the citation of the relevant statutes provided in secondary sources, the authors — one of whom has formal legal training — retrieved the full texts of the current statutes and their historical versions from online legal databases Westlaw and Hein Online. The laws in the Tables below that do not indicate a secondary source were obtained entirely based on original legal research undertaken by the authors.

Table AI

Selected laws in the domain of alcohol regulation used in analysis. The number of states enacting related laws in 1980–2010 is given in parentheses.

Domain	Policy	Law	Source
Alcohol Regulation	Beer tax	State excise tax on packaged beer (30)	[78]
	Dramshop liability	What kind of knowledge/action by the vendor is required for there to be liability in civil action (20)	
		What kind of knowledge/action by the vendor is required for there to be liability under criminal or administrative law (8)	

Domain	Policy	Law	Source
		What kind of responsibility is imposed upon the liable vendor (32)	
	Host liability	Presence of laws that impose liability against individual social hosts responsible (23)	[79]
		Whether the law applies to underage parties or all parties (24)	[79]
		Whether the law applies to residential, outdoor, or other properties (24)	[79]
		Whether the law holds hosts responsible based on underage guests; consumption of alcohol, or if possession is enough (24)	[79]
		Whether the law exempts family members and/or non-owner residents of the property (24)	[79]
	Keg registration	Presence of regulations for registering purchased kegs (31)	[80, 81]
	Alcohol sales ban on Sundays	Presence of a law prohibiting purchase of alcohol on Sundays (7)	[82]

Table A2

Selected laws in the domain of general driving safety regulations used in analysis. The number of states enacting related laws in 1980–2010 is given in parentheses.

Domain	Policy	Law	Source
General Driving Regulation	Distracted driving	Restrictions on cell phone talking while driving (32)	[83]
		Restrictions on texting while driving (39)	[83]
		Primary Enforcement of talking and texting restrictions (38)	[83]
	Driver protection	Presence of a law that requires safety belt use for all passengers (49)	[84–86]
		Primary enforcement of seatbelt law for everyone in the car (34)	[86]
		Maximum fine for seatbelt non-use (1st offense) (49)	[86]
		Presence of a law that decreases monetary awards for injuries in lawsuits for seatbelt non-use (16)	[86]
	Graduated Driver's License (GDL) programme	Minimum entry age or learner's permit (50)	[87]
		Required minimum number of days one must hold a learner's permit (50)	[87]
		Required minimum hours of supervised driving (44)	[87]
		Required minimum hours of supervised driving after completing driver education (40)	[87]
		Required minimum hours of night time or inclement weather practice hours (37)	[87]
		Minimum age at which one can obtain a license (50)	[87]

Domain	Policy	Law	Source
		Whether night time unsupervised driving is restricted with a learner's permit (48)	[87]
		Earliest time at which nighttime driving restriction may be lifted (33)	[87]
		Minimum age at which night time driving restriction may be lifted (48)	[87]
		Enforcement priority for GDL nighttime driving restriction law (48)	[87]
		Whether the state bans teenage passengers for a certain period (15)	[87]
		Minimum age at which a driver can have a teenage passenger in the vehicle (15)	[87]
		Enforcement priority for GDL teenage passenger restriction law (15)	[87]
	Child restraints	Whether use of a child restraint is regulated (49)	[88]
		Whether use of a child restraint for infant passengers is regulated (50)	[88]
		Whether use of a child restraint for toddlers is covered (50)	[88]
		Whether use of a child restrain is covered for booster seat age children (48)	[88]
		Primary enforcement of child restraint laws (49)	[88]
		Whether children must be seated in the back of the vehicle (15)	[88]
		Primary enforcement of rear seating for children (13)	[88]

Table A3

Selected laws in the domain of impaired driving regulations used in analysis. The number of states enacting related laws in 1980–2010 is given in parentheses.

Domain	Policy	Law	Source
Impaired Driving Regulation	Open container	Whether open containers of alcohol are banned in MV passenger compartments (34)	[89]
	Zero tolerance	Whether a zero tolerance law applies (50)	[90]
		The age below which zero tolerance law applies (50)	[90]
		The BAC level for charging offender under zero tolerance law (50)	[90]
	DUI penalties	Blood alcohol concentration level above which a person is presumed to have been driving under the influence (49)	[90]
		Whether imprisonment is part of mandatory penalty for first-time DUI offenders (24)	
		Minimum number of days the first-time DUI offender must serve in prison (27)	
		Whether imprisonment is part of mandatory penalty for second-time DUI offenders (30)	

Domain	Policy	Law	Source
		Minimum number of days the second-time DUI offender must server in prison (36)	
		Whether penalty license suspension is mandatory for first-time DUI offenders (30)	
		The minimum number of days the licenses of the first-time DUI offender must be suspended (38)	
		Whether penalty license suspension is mandatory for second-time DUI offenders (32)	
		The minimum number of days the licenses of the second-time DUI offender must be suspended (39)	
		Whether a fine is mandatory for first-time DUI offenders (26)	
		Minimum fine for first-time DUI offenders (45)	
		Whether a fine is mandatory for second-time DUI offenders (28)	
		Minimum fine for second-time DUI offenders (43)	

Appendix B

Estimation of model parameters from real law activity data

In estimating the parameters a and β in (3.8) from real law activity data, the enactment events $x_{ik}(t)$ must be attributable to one of the pathways to enactment depicted in Figure 2. However, for the real regulation time series, it is not known in advance which events are due to the law history of a state's neighbors and which are due to internal processes. Under this incomplete-data scenario, we employ the expectation maximization algorithm [63] to estimate the parameters α and β from the law enactment data. We introduce a latent variable $\theta_{ik}(t)$ that takes value 1 if any neighbor $j \in \mathscr{N}_i$ has made a change in law k in the last $\tau_{ik}(t)$ days, and value 0 otherwise. The probability $P(\theta_{ik}(t) = 1)$ is denoted γ. The full conditional likelihood of $[x_{11}(1), \ldots, x_{NK}(T)]$ and $[\theta_{11}(1), \ldots, \theta_{NK}(T)]$ can be written as

$$P(x_{11}(1),\ldots,x_{\mathrm{NK}}(T),\theta_{11}(1),\ldots,\theta_{\mathrm{NK}}(T)|\alpha,\beta,\gamma)=\prod_{i=1}^{N}\prod_{k=1}^{K}\prod_{t=1}^{T}[\alpha\beta+\theta_{\mathrm{ik}}(t)\alpha(1-\beta)]^{x_{\mathrm{ik}}(t)}$$
$$\times\,[1-\alpha+(1-\theta_{\mathrm{ik}}(t))\alpha(1-\beta)]^{1-x_{\mathrm{ik}}(t)}$$
$$\times\,\gamma^{\theta_{\mathrm{ik}}(t)}[1-\gamma]^{1-\theta_{\mathrm{ik}}(t)}.$$

(5.1)

The estimation step [63] yields an update as

$$\theta_{\mathrm{ik}}(t) \leftarrow \mathbb{E}_{\theta_{11}(1),\ldots,\theta_{\mathrm{NK}}(T)|x_{11}(1),\ldots,x_{\mathrm{NK}}(T),\alpha,\beta,\gamma}[\theta_{\mathrm{ik}}(t)] = \sum_{\theta_{\mathrm{ik}}(t)} \theta_{\mathrm{ik}}(t) P(\theta_{\mathrm{ik}}(t)|x_{11}(1),\ldots,x_{\mathrm{NK}}(T),\alpha,\beta,\gamma)$$
$$= \gamma\alpha^{x_{\mathrm{ik}}(t)}(1-\alpha)^{1-x_{\mathrm{ik}}(t)}.$$

(5.2)

For the maximization step, we numerically maximize the sum of the log likelihood and a linear penalty on β:

$$(\alpha,\beta,\gamma) \leftarrow \arg\max_{\alpha,\beta,\gamma}[\log(P(x_{11}(1),\ldots,x_{\mathrm{NK}}(T),\theta_{11}(1),\ldots,\theta_{\mathrm{NK}}(T)|\alpha,\beta,\gamma))]+1000\beta.$$

(5.3)

The penalty on β is selected to avoid having the EM algorithm attribute all law enactment events to random internal processes (with $\alpha = \Sigma_{i,k,t}\, x_{ik}(t)/NKT$) and $\beta = 1$). We fit the law enactment data corresponding to the alcohol regulation domain (Table A1) to the model, resulting in parameter estimates $\alpha = 1.58 \times 10^{-4}$ and $\beta = 0.613$.

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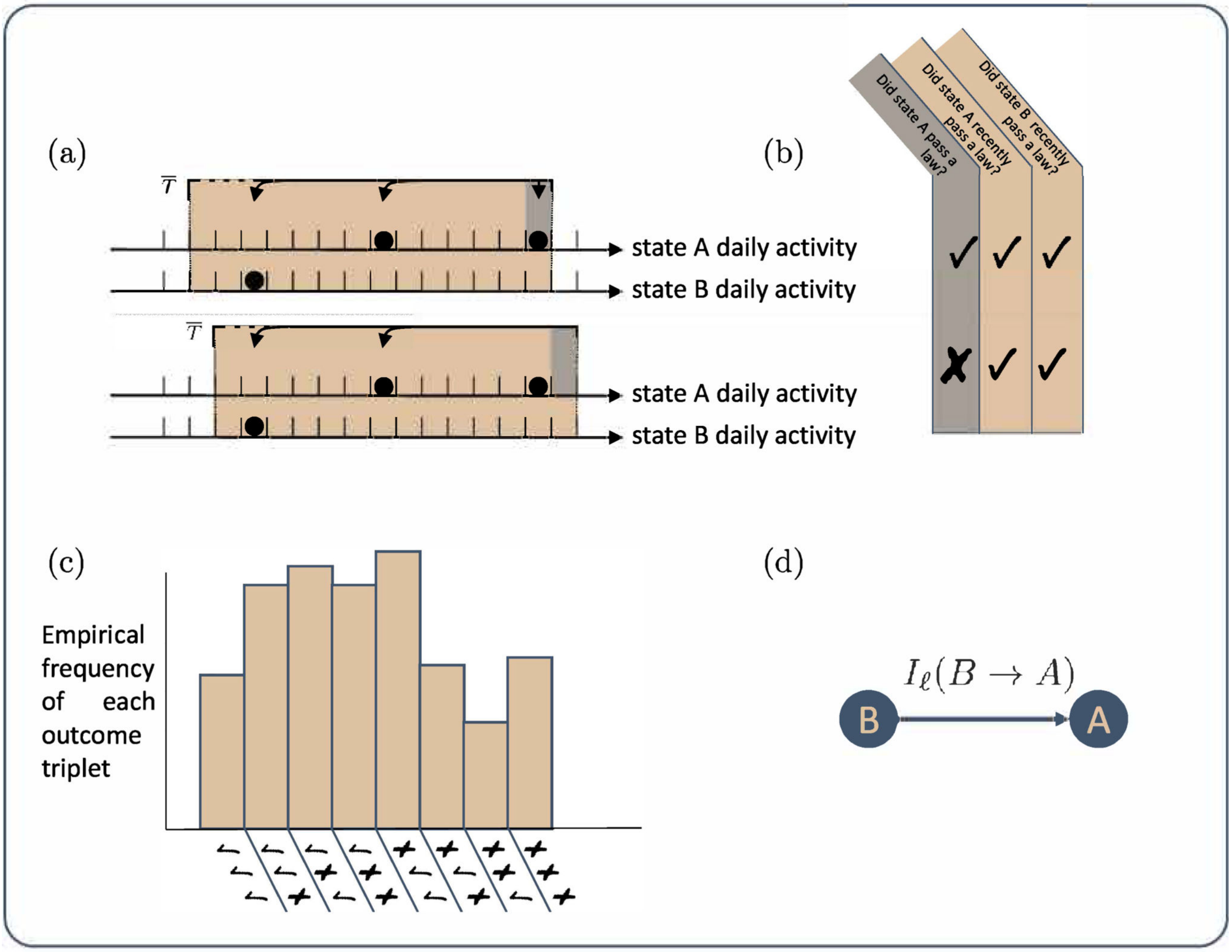

Figure 1.

Process for computing union transfer entropy. (a) A sliding window considers the activity in state A (grey), the union of all activity in a historical period in state A (beige), and the union of all activity in the same historical period in state B (beige). (b) The outcome is tabulated for each position of the sliding window. (c) A histogram of the frequency of each possible outcome is computed based on the available data as in Equation (3.1). (d) The (union transfer entropy-based) influence from state B to state A is computed based on these probabilities as in Equation (3.2).

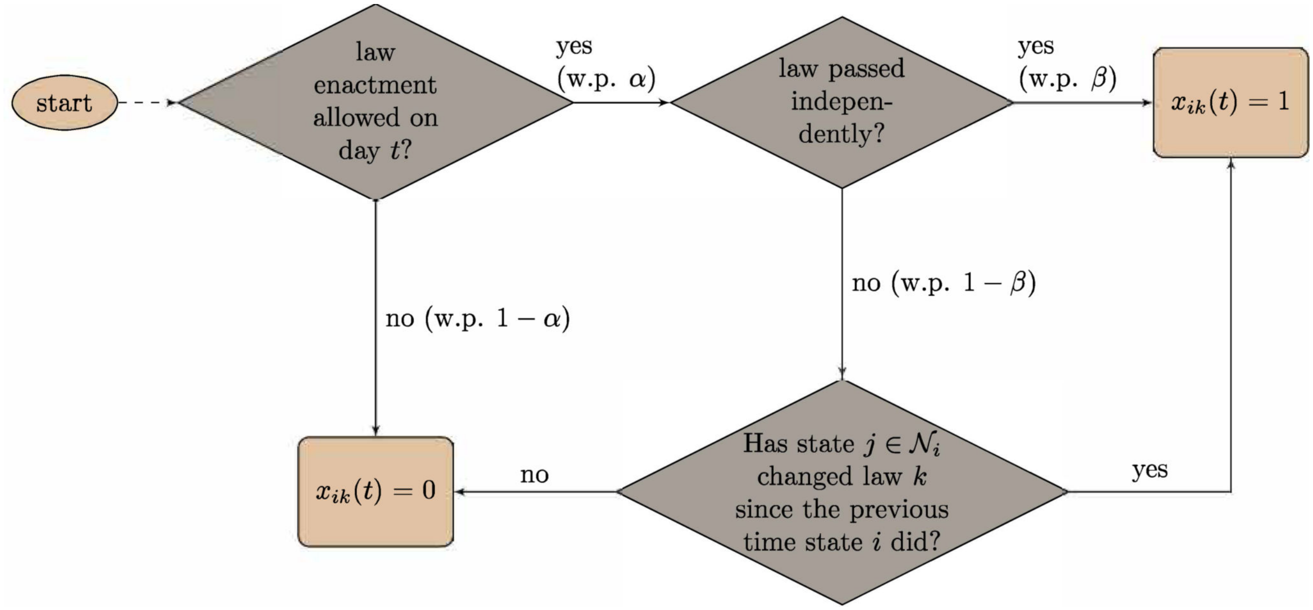

Figure 2.

Flowchart depicting the possible outcomes of $x_{ik}(t)$ based on the history of law k in state i and its connected neighbors $j \in \mathcal{N}_i$ where w.p. stands for with probability. The pathway for $x_{ik}(t)$ is determined by the probabilities α and β, as well as the law activity in states $j \in \mathcal{N}_i$, for law k.

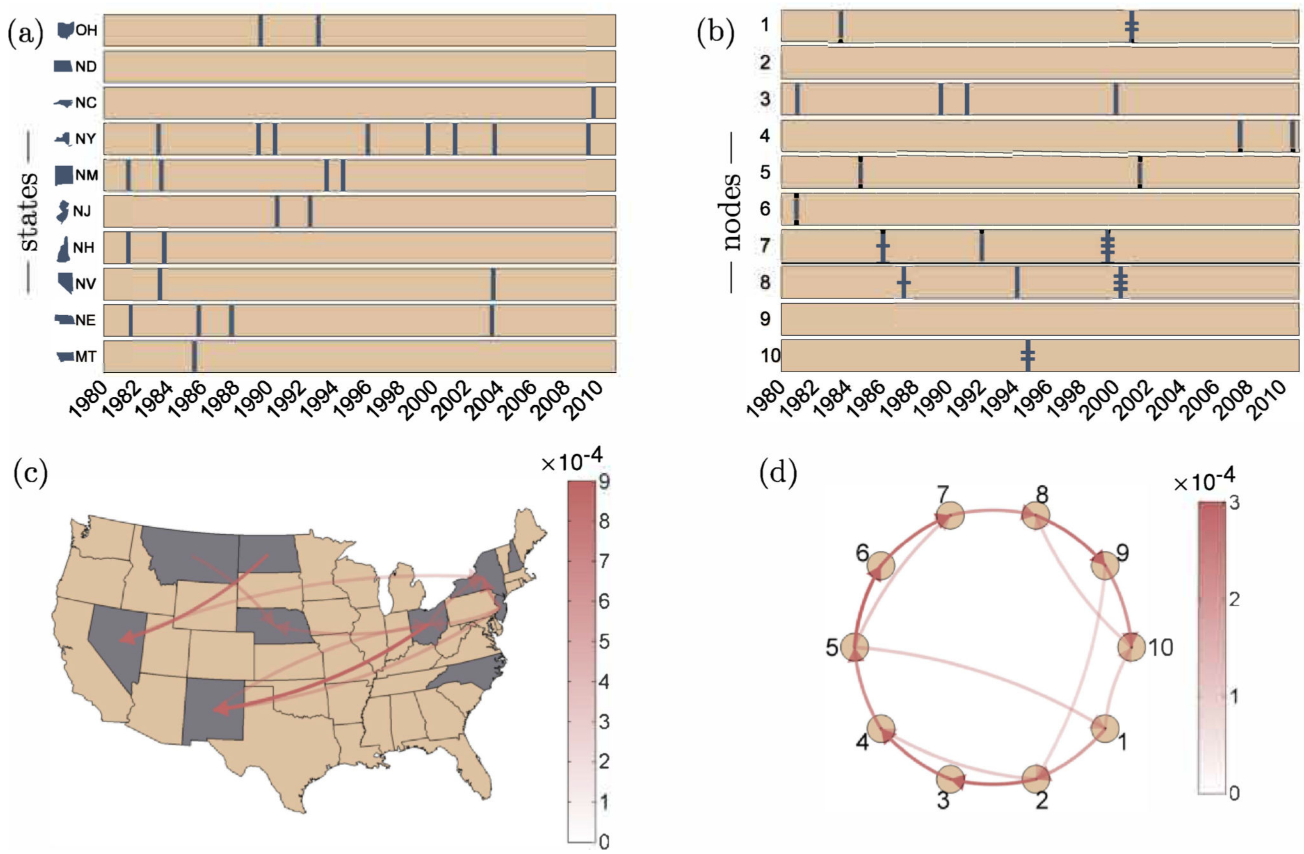

Figure 3.

Law activity of the beer tax rate of a sequence of 10 states selected at random but in alphabetical order (a) and simulated data (b). Each vertical line corresponds to the occurrence of law activity, and the absence of a line indicates no activity for each day t in 1980–2010. Simulated enactments in (b) are based on an underlying network in which state 1 influences state 2, state 2 influences 3, and so on (a ring-like topology). Pairs of law enactments that occurred due to a causal interaction are highlighted in one, two, and three hatch marks; for example, node 7 influences node 8 around 1988 and again, independently, in 2001. Corresponding reconstructed networks (c)–(d), with edge opacity selected from the strength of union transfer entropy computed using data for K = 11 laws. Edges are directed, as indicated by arrow heads and the curvature of the edges; for clarity, only edges in the 85^{th} percentile are drawn. The graph edit distance [66] between the ring-like graph and the unweighted version of (d), which is the proportion of edge edits required to transform one graph to the other, is 5. 6%.

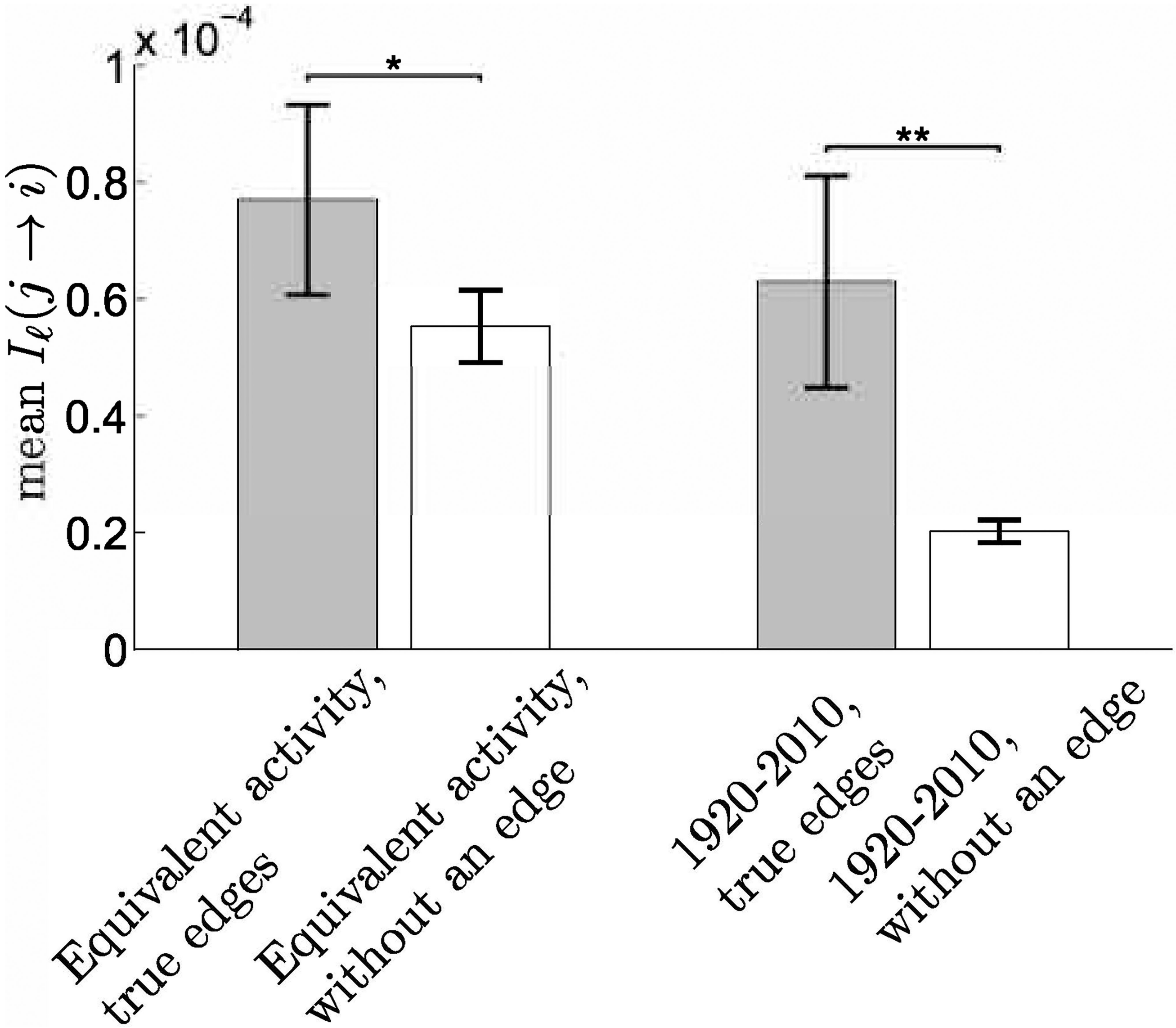

Figure 4.

Measured influence $I_\ell(j \to i)$ for simulated data in Fig. 3(b), and for data with the same rate as Fig. 3(b) but for years 1920–2010 (91 years). Grey bars indicate information flow measured for two states that are connected in the known underlying network, and white estimates correspond to states that are not connected. Asterisks * and ** indicate significance at the $p < 0.05$, and $p < 0.01$ levels, respectively. Error bars denote standard error.

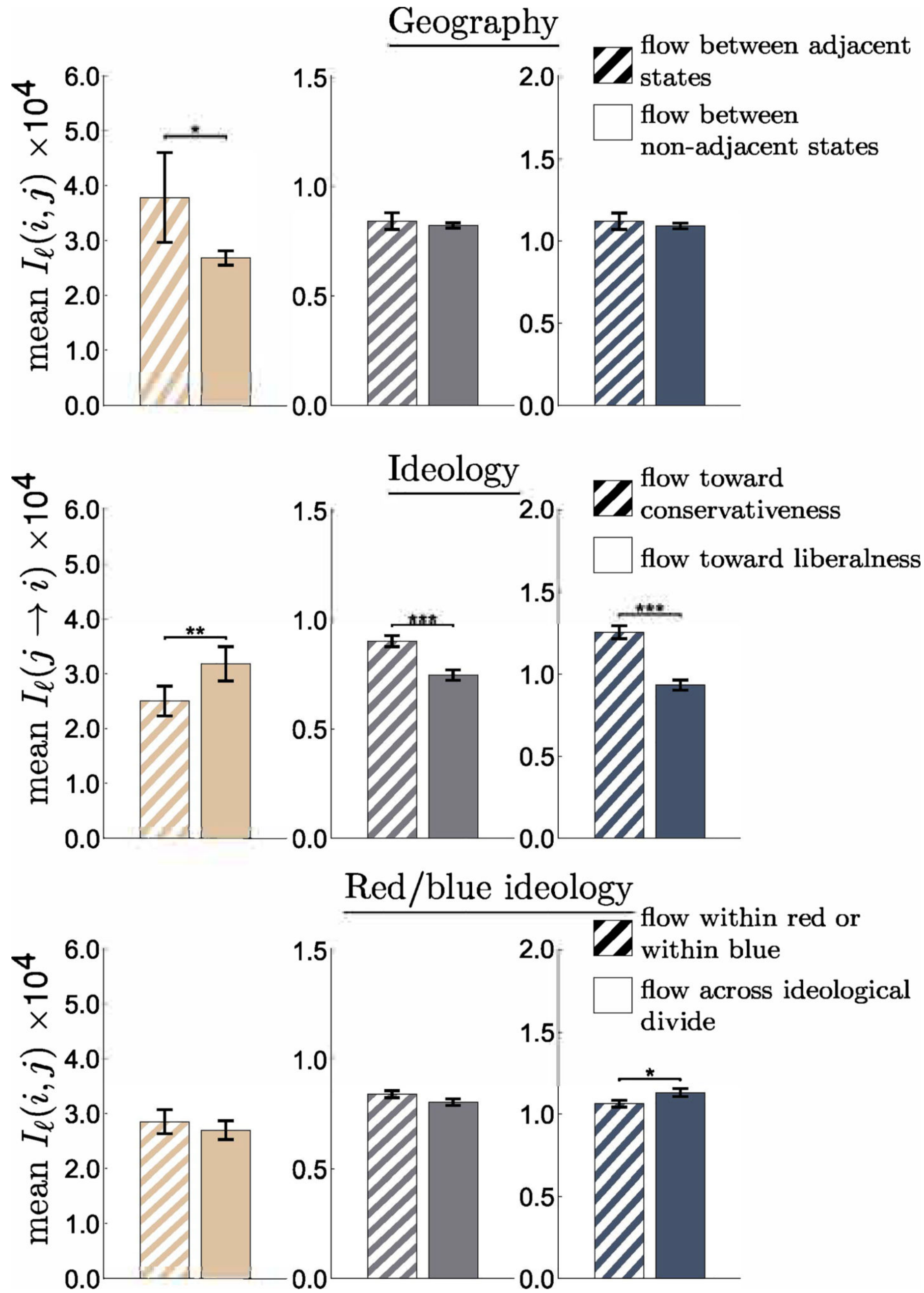

Figure 5.

Information flows between adjacent states and toward liberal states in the realm of alcohol regulation, while both driving and impaired driving regulations flow toward conservative states. Mean influence $I_\ell(i, j)$ or directed influences $I_\ell(j \to i)$ for alcohol (left), driving (middle), and impaired driving (right) law domains are clustered by state geographical and ideological similarity. Asterisks *, **, and *** indicate significance at the $p < 0.05$, $p < 0.01$, and $p < 0.001$ level, respectively. Error bars denote the standard error.

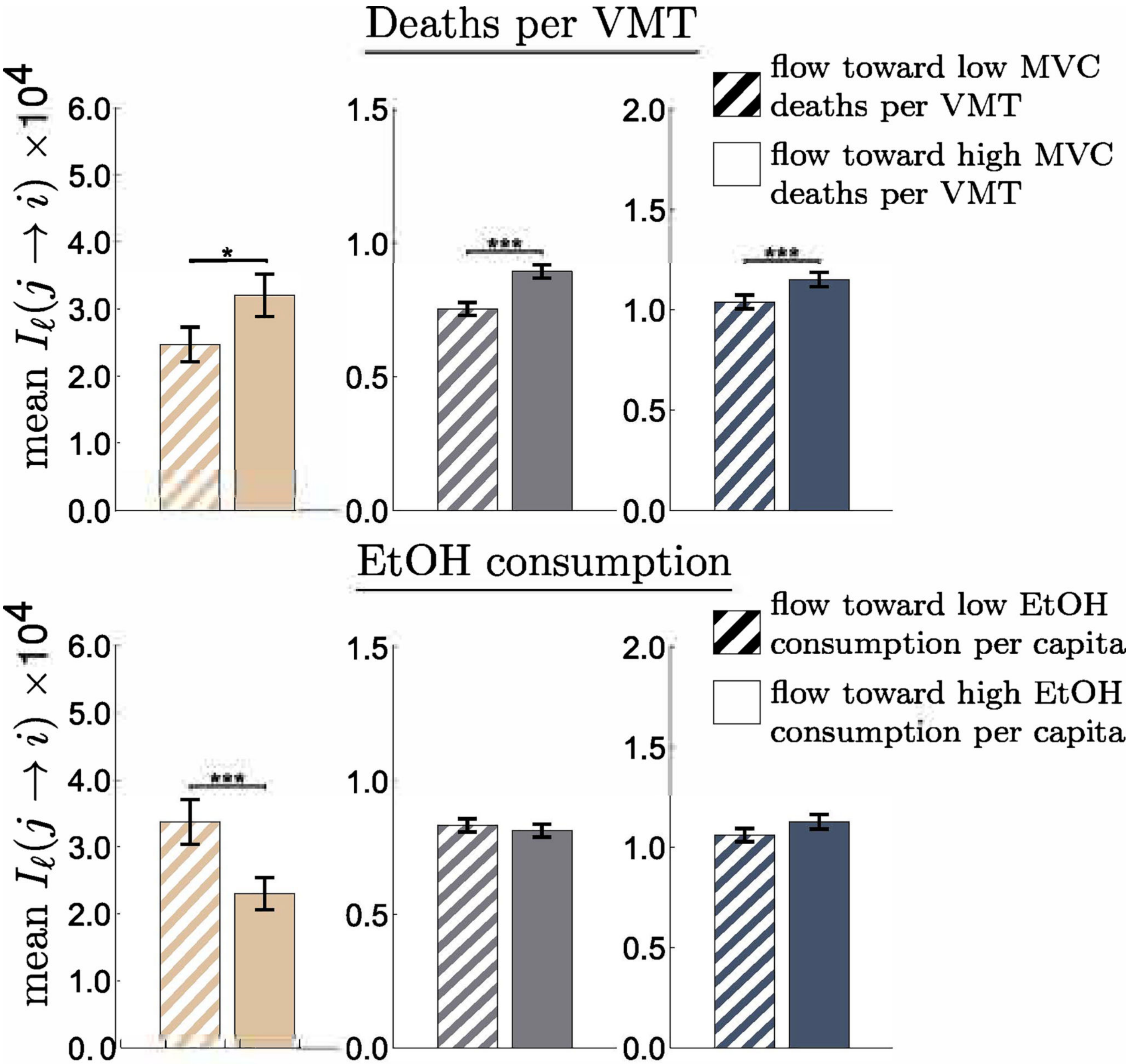

Figure 6.

Influence in alcohol, driving, and impaired driving flows towards states with a higher MVC death rate. Mean directed influences $I_\ell(j \to i)$ are clustered by health outcomes, organized in the same manner as Fig. 5.

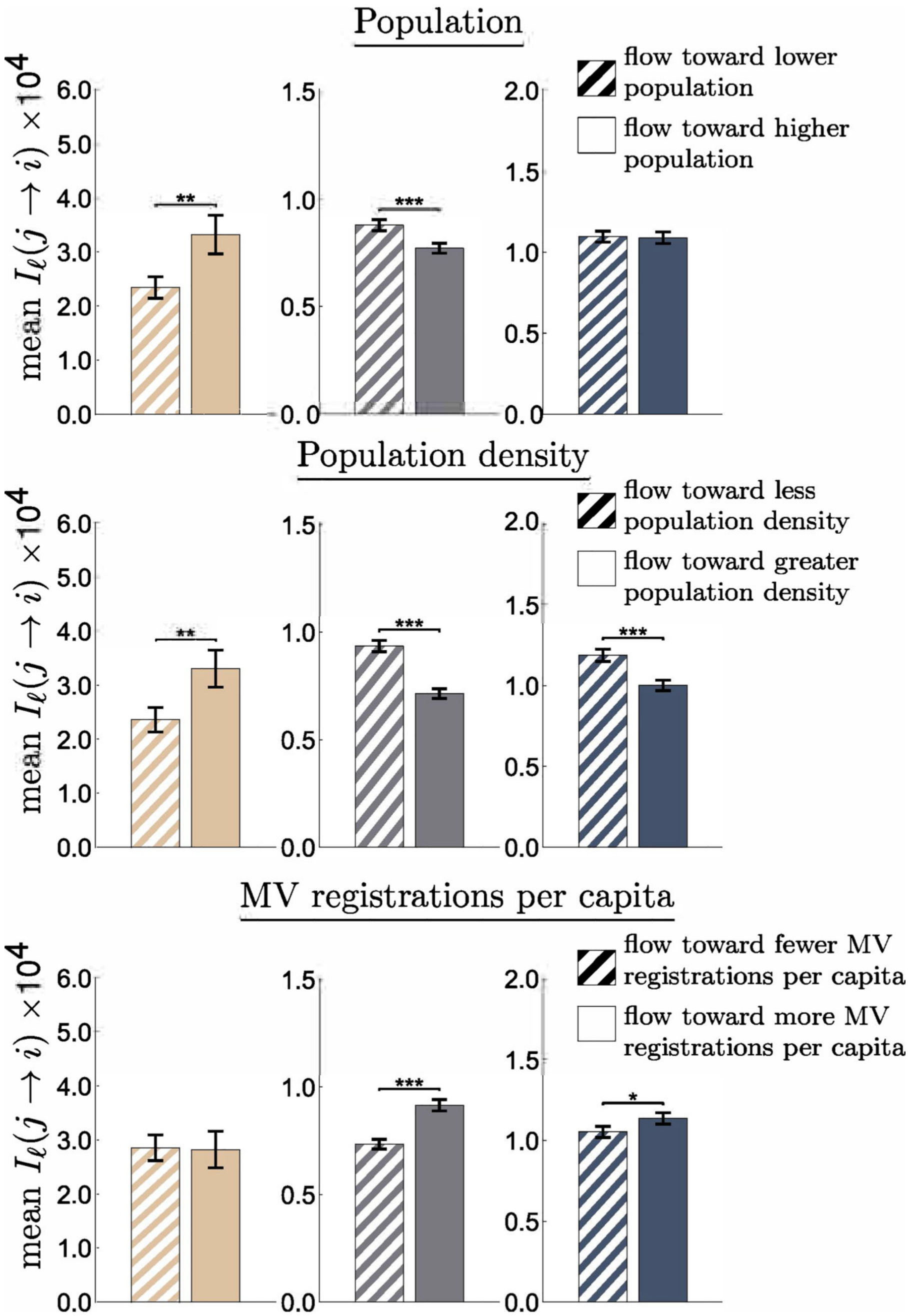

Figure 7.

The direction of flow for driving and impaired driving often differs from the directions found in alcohol policy. Mean directed influences $I_\ell(j \to i)$ are clustered by population, organized in the same manner as Fig. 5

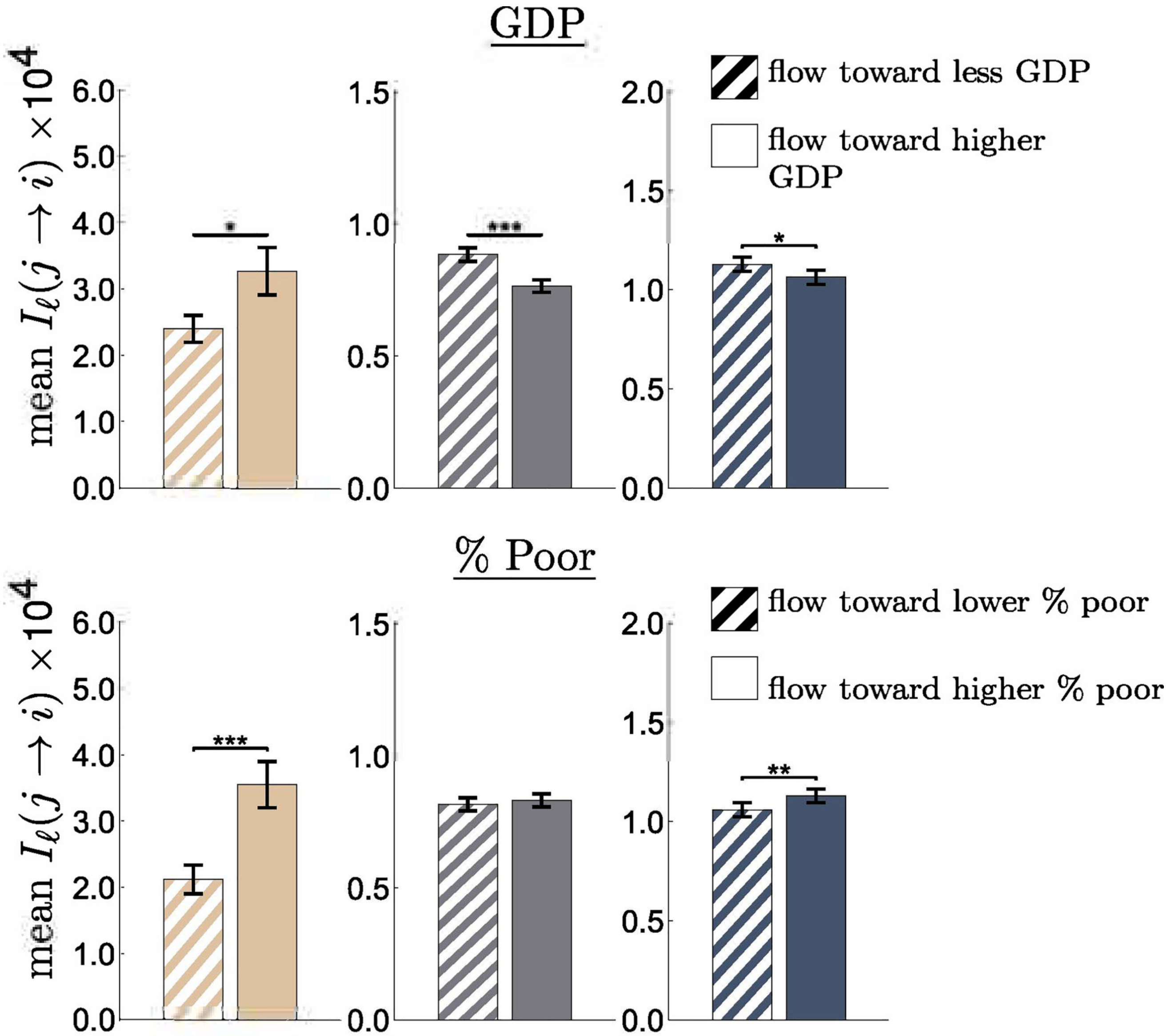

Figure 8.

Driving and impaired driving regulations flow toward states with a lower GDP. Mean directed influences $I_\ell(j \to i)$ are clustered by economic indicators, organized in the same manner as Fig. 5.

Table 1

Measures of dissimilarity between states.

Dissimilarity	Description	Clustered by	Ref.
Geographical $\upsilon_G(i, j)$	Smallest number of border crossings required to travel from one state to another	Whether states are adjacent ($\upsilon_G(i, j) = 1$)	
Ideological $\upsilon_I(j \rightarrow i)$	Total difference between the political ideology of state i from state j over the years 1980–2010, $\upsilon_I(j \rightarrow i) = \Sigma_{\text{year } r}\,\text{ideology}_i(r) - \text{ideology}_j(r)$, based on the average ideological position of that state's elected officials, including the governor and the major party delegations in each house of the state's legislative bodies.	If state j is, on average, more liberal / conservative ($\upsilon_I(j \rightarrow i) > 0$ / $\upsilon_I(j \rightarrow i) < 0$)	[50]
Red/blue distance $\upsilon_{R/B}(i, j)$	If two states are on average on different sides of the ideological divide (the mean ideology in a given year) over 1980–2010	Whether states are more often than not on different sides ($\upsilon_{R/B}(j \rightarrow i) = 1$).	[50]
Motor vehicle deaths $\upsilon_D(j \rightarrow i)$	Difference between the sum over 1980–2010 of the number of deaths due to MVCs per vehicle miles traveled (VMT) in state i and that of state j	Whether state j has higher / lower total deaths per VMT ($\upsilon_D(j \rightarrow i) > 0$ / $\upsilon_D(j \rightarrow i) < 0$)	[51]
Alcohol consumption $\upsilon_A(j \rightarrow i)$	Difference between the sum over 1980–2010 of the gallons of ethanol consumed per capita (≥ 21 years) consumed in state i and that of j	Whether state j consumes in total more / less EtOH ($\upsilon_A j \rightarrow i > 0$ / $\upsilon_A(j \rightarrow i) < 0$)	[52]
Population size $\upsilon_P(j \rightarrow i)$	Sum over 1980–2010 of the difference in total populations of states i and j	Whether state j has a higher/lower population on average ($\upsilon_P(j \rightarrow i) > 0$ / $\upsilon_P(j \rightarrow i) < 0$)	[53–55]
Population density $\upsilon_{PD}(j \rightarrow i)$	Sum of the differences over 1980–2010 of the total population per square mile of the state i and that of j	Whether j has higher / lower population density on average ($\upsilon_{PD}(j \rightarrow i) > 0$ / $\upsilon_{PD}(j \rightarrow i) < 0$)	[54, 55]
Motor vehicle registration rate $\upsilon_V(j \rightarrow i)$	Sum over 1980–2010 of the differences in the number of motor vehicle registrations per capita in states i and j	Whether j has on average higher / lower registered vehicles per capita than i ($\upsilon_V(j \rightarrow i) > 0$ / $\upsilon_V(j \rightarrow i) < 0$)	[56]
Gross domestic product (GDP) $\upsilon_{GDP}(j \rightarrow i)$	Sum over 1980–2010 of the differences of the GDPs of states i and j	Whether j has higher / lower GDP on average than state i ($\upsilon_{GDP}(j \rightarrow i) > 0$ / $\upsilon_{GDP}(j \rightarrow i) < 0$)	[57]
Percent state population below poverty threshold $\upsilon_{\%P}(j \rightarrow i)$	Sum of the differences in the percentage of people with yearly income below the federal poverty line for states i and j	Whether j has a higher / lower percentage of poor than i ($\upsilon_{\%P}(j \rightarrow i) > 0$ / $\upsilon_{\%P}(j \rightarrow i) < 0$)	[53]

Table 2

Pearson correlation coefficients R between different dissimilarity measures applied to all pairwise combinations of 50 states. Significant correlations ($p < 0.05$) appear in bold.

	More liberal	**Higher death rate**	**More Et OH**	**More pop.**	**More pop. density**	**More MV regs.**	**Higher GDP**	**More % poor**
More liberal	1	**−0.35**	**0.04**	0.03	**0.47**	**−0.43**	**0.07**	**−0.13**
Higher death rate	**−0.35**	1	**−0.05**	**−0.19**	**−0.56**	**0.07**	**−0.23**	**0.74**
More EtOH	**0.04**	**−0.05**	1	**−0.11**	0.02	**0.06**	**−0.08**	**−0.41**
More pop.	0.03	**−0.19**	**−0.11**	1	**0.19**	**−0.33**	**0.99**	**0.13**
More pop. density	**0.47**	**−0.56**	0.02	**0.19**	1	**−0.36**	**0.22**	**−0.33**
More MV regs.	**−0.43**	**0.07**	**0.06**	**−0.33**	**−0.36**	1	**−0.33**	**−0.13**
Higher GDP	**0.07**	**−0.23**	**−0.08**	**0.99**	**0.22**	**−0.33**	**1**	**0.09**
More% poor	**−0.13**	**0.74**	**−0.41**	**0.13**	**−0.33**	**−0.13**	**0.09**	1