

# Policy Diffusion: The Issue-Definition Stage

Fabrizio Gilardi\*

Charles R. Shipan<sup>†</sup>

Bruno Wueest<sup>‡</sup>

October 10, 2018

9,905 words

## Abstract

We put forward a new approach to studying issue definition within the context of policy diffusion. Most studies of policy diffusion—which is the process by which policymaking in one government affects policymaking in other governments—have focused on policy adoptions. We shift the focus to an important but neglected aspect of this process: the issue-definition stage. We use topic models to estimate how policies are framed during this stage and how these frames are predicted by prior policy adoptions. Focusing on smoking restriction in U.S. states, our analysis draws upon an original dataset of over 52,000 paragraphs from newspapers covering 49 states between 1996 and 2013. We find that frames regarding the policy’s concrete implications are predicted by prior adoptions within a state’s diffusion network, while frames regarding its normative justifications are not. Our approach and findings open the way for a new perspective to studying policy diffusion in many different areas.

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\*Department of Political Science, University of Zurich (<http://www.fabriziogilardi.org/>).

<sup>†</sup>Department of Political Science, University of Michigan ([cshipan@umich.edu](mailto:cshipan@umich.edu)).

<sup>‡</sup>Department of Political Science, University of Zurich (<http://www.bruno-wueest.ch/>).

# 1 Introduction

When states or nations adopt new policies, their decision to adopt can be influenced not only by internal factors, but also by external factors, a process often referred to as *policy diffusion* (Simmons et al., 2006; Braun and Gilardi, 2006; Graham et al., 2013). However, if policies do diffuse, they would not spread directly from adoption in one place to adoption in another, as most studies have suggested. Rather, the path would flow from adoption in one place to the *beginning* of the policy process—the issue-definition stage—in another. After all, policymaking proceeds in several stages, starting with the identification and definition of an issue, and then only later (potentially) culminating in an adoption.

In this paper we examine whether and how prior adoptions predict the way an issue is defined, or framed, in other states.<sup>1</sup> Regardless of whether consideration of a policy in later governments results in an adoption, policy ideas can spread from one unit to another. Adoptions are rare, whereas consideration of new policies occurs frequently; and issues can be defined in a variety of ways. To this end, in our analysis we treat issue definition as an outcome and examine whether and how previous policy adoptions predict how an issue is defined.<sup>2</sup>

We begin by using structural topic models (Roberts et al., 2016) to estimate how policies are defined. Applying this technique to an original dataset of 52,000 newspaper paragraphs about antismoking laws in the US states reveals how this issue has been defined and how this framing has evolved. Our approach demonstrates the usefulness of automated text analysis for measuring issue definition based on a large number of articles across dozens of newspapers over time.

Based on this approach, we analyze whether the prevalence of these issue definitions is predicted by earlier policy adoptions. To structure this analysis, we draw upon research that identifies, for each state, the other states that constitute its diffusion network (Desmarais et al., 2015). This allows us to examine the link between issue definitions in a state and prior adoptions by other states within that state’s diffusion network. Controlling for many relevant factors, we find that some frames used to describe smoking restrictions in a given state are predicted by the

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<sup>1</sup>We use the terms *issue definition* and *policy framing* interchangeably throughout the paper.

<sup>2</sup>In other words, we analyze policy-to-frame diffusion, not frame-to-frame-diffusion. We elaborate on this point in the conclusion

prevalence of the policy within that state's diffusion network. We also build on theoretical studies regarding the mechanisms of diffusion to understand why some issue definitions are subject to diffusion, while others are not (Braun and Gilardi, 2006; Shipan and Volden, 2008). In particular, we examine expectations related to two mechanisms, learning and emulation. We find that issue definitions are predicted by prior adoptions in topics where learning can occur, that is, in topics that refer to concrete, observable aspects of the policy. In contrast, when we examine the mechanism of emulation, we find that two prominent normative frames—individual rights (i.e., freedom and health)—are not predicted by prior adoptions.

Finally, after demonstrating the connection between issue definition and prior adoptions, and examining the role of diffusion mechanisms, we then explore whether individual frames occur in combination with each other. Our main analysis considers individual topics, as these constitute “the smallest units of framing” (Baumgartner et al., 2008, 107). But in addition to allowing us to identify simple frames, individual topics also can serve as building blocks, with topics combining to create more complex frames. This method allows us to determine which topics occur together, giving us a view of how and when complex frames occur. The analysis shows that the complexity of frames increases as the policy becomes more widespread.

Our analysis yields several notable contributions. First, we show why and how studies of policy diffusion should take the issue-definition stage into account. Second, our analysis demonstrates that diffusion is related to the way smoking bans are framed in areas in which information on the policy's concrete implications emerges from earlier adoptions in other states, whereas normative justifications, such as individual rights and public health, are less susceptible to change following policy diffusion. Third, we show how the focus on issue definition broadens the ability to study diffusion. Adoptions are relatively infrequent events, with not all policymaking efforts resulting in new policies, or even in concrete policy proposals. That is, adoptions either happen or do not happen, and can be rare. Consideration of new policies, on the other hand, occurs frequently; and issues can be defined in a variety of ways. Thus, attention to the link between prior adoptions and the ways in which issues are defined and framed in other states provides scholars with more leverage to study policy diffusion.

## 2 Theoretical Background

Our goals are to determine whether and how previous adoptions predict issue definition. We proceed in three steps. First, we explore existing studies that are relevant for our analysis and that explain why examining the connection between previous adoptions and later issue definitions is so imperative. Second, we explain how the literature on framing is relevant for this analysis and then show how our use of topic models provides us with an appropriate way of addressing issue definition. Third, we develop a framework that provides a theoretical foundation for our empirical work.

### 2.1 Policy Diffusion and Issue Definition

We situate our study directly within the literature on diffusion. Most studies of diffusion have focused on policy adoptions as both an independent variable and a dependent variable—that is, whether earlier policy adoptions influence the likelihood of later policy adoptions (e.g., [Berry and Berry, 1990](#); [Boehmke and Witmer, 2004](#)). Yet although it is well recognized that policies pass through several stages before reaching the adoption stage, few diffusion studies have considered the relationship between prior adoptions and these earlier stages.<sup>3</sup>

Policies advance through a series of stages, including several stages that necessarily occur prior to adoption (e.g., [Anderson, 2014](#); [Patton et al., 2015](#)). At the start of the policymaking process—before policy alternatives are placed on the agenda, before policy issues are formulated, before adoption can take place—issues need to be identified and defined. Indeed, as [Elder and Cobb \(1984, 115\)](#) cogently observed, because “policy problems are not a priori givens but rather are matters of definition [...] what is at issue in the agenda-building process is not just which problems will be considered but how those problems will be defined.” Hence, issue definition is a logical starting point for the policymaking process; and if diffusion does occur, we should expect to see it in the form of prior adoptions predicting how issues are defined.

Although there are countless studies of issue definition, from the viewpoint of policy dif-

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<sup>3</sup>[Pacheco \(2012\)](#) and [Karch \(2007\)](#) are two exceptions.

fusion Boushey's (2016) innovative investigation of the adoption of criminal justice policies is the closest to ours, in that he examines the importance of issue definition within a policy diffusion framework. However, our study and his have opposite explanatory concerns: he looks at how the definition (or more specifically the social construction) of an issue affects its diffusion, whereas we focus on how diffusion can produce different issue definitions over time and across governments. Thus, our study and his are complementary, with Boushey examining how frames can lead to adoptions, while we investigate how adoptions can predict frames.

## 2.2 Issue Definition and Policy Frames

We first specify what we mean by *framing* and *issue definition*. Most directly, policy frames can be defined as “the presentation or discussion of an issue from a particular viewpoint to the exclusion of alternate viewpoints” (Baumgartner et al., 2008, 106).<sup>4</sup> In other words, these frames or issue definitions tell us how a policy problem is perceived or understood at any given time (Baumgartner and Jones, 1993). Because policies are almost always multidimensional, it is neither automatic nor obvious that a policy will be defined in a particular way, or that this frame will remain constant over time. Instead, we argue that these frames can be predicted by earlier actions taken by other states.

Why should we care about how a policy is framed or defined? To begin with, by emphasizing some aspects of a policy problem and not others, policy frames “defin[e] the range of relevant problems to be addressed and [provide] the fundamental categories that shape decision making” (Steensland, 2008, 2). Hence, how a policy is defined at the start of the process can affect whether and how it will be addressed. A debate over health care, for example, is likely to lead to very different policy outcomes if it is defined primarily as a matter of limiting government control over personal autonomy than if it is framed as a problem of lack of access to quality health care. Furthermore, these frames can change over time, with one frame being dominant at one time (and in one place) and other frames taking over later. When frames change over time, they can be understood as a “storyline or unfolding narrative about an issue” (Gamson et al., 1992, 385).

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<sup>4</sup>This simple definition is consistent with many others (e.g., Entman 1993, 52; Druckman 2004, 672).

These definitions and changing narratives can have important implications, with changes in issue definitions and frames producing shifts in the agenda (Kingdon, 1984; Wolfe et al., 2013) and leading to other downstream effects. For example, issue definition can influence the ways in which policy alternatives are designed during the formulation stage of the policy process (Wildavsky, 1987). Baumgartner and Jones (1993) further establish that how an issue is defined can influence the policies that are ultimately enacted, with changes in issue definition potentially leading to the punctuation of policy equilibria. Indeed, the effect of issue definition on later stages in the policymaking process, including adoption, is “nearly axiomatic” within the policymaking literature (Boushey, 2016, 200).

Several analyses have demonstrated not only that public policies can be framed in different (and competing) ways, but also that the choice of policy frames can influence subsequent stages of the policy process. One of the best-known studies of policy framing is Baumgartner, De Boef, and Boydston’s (2008) investigation of the death penalty.<sup>5</sup> Drawing on hand-coded abstracts of *New York Times* articles about the death penalty, they establish that the dominant frame of this issue changed dramatically over time, with frames relating to constitutionality and morality giving way to an emphasis on the potential innocence of convicts who were sentenced to death. They also show that this shift produced changes in public opinion and in policy outcomes, as measured by the number of death sentences.

As we will discuss in detail in Section 3.3, our approach identifies frames empirically using topic models, which means that we consider the topics uncovered by these models as an operationalization of policy frames. Here, we follow DiMaggio et al. (2013) and Nowlin (2016), who argue that topic models are an ideal tool to identify frames in texts. Specifically, DiMaggio et al. (2013, 578, 593) write that “[m]any topics may be viewed as frames...and employed accordingly....[T]opic modeling has some decisive advantages for rendering operational the idea of ‘frame.’” Such topics can be used individually to show simple frames, or can be combined to

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<sup>5</sup>Other notable studies of framing have examined immigration (Haynes et al., 2016), agriculture (Bosso, 2017), and birth control (VanSickle-Ward and Wallsten, 2017). Closer to the empirical focus of our paper, several studies have shown that the success of tobacco policies is closely linked to their framing (e.g., Menashe and Siegel, 1998; Harris et al., 2010).

show larger and more complex frames (Baumgartner et al., 2008).<sup>6</sup> Our approach focuses primarily on the building blocks of frames (or subframes) with which more complex frames might be constructed. However, our analysis will also provide information on the ways in which the individual topics are connected to form more complex frames.

### 2.3 Theoretical Expectations

The logic for why a diffusion process might occur between earlier adoptions and later frames is similar to the logic scholars have used to explain adoption-to-adoption diffusion. If a state has not yet adopted a policy, politicians in that state, along with staffers, the media, interest groups, and other relevant political actors, will look to see what other states have done. They will observe which states have adopted policies and which have not. They will observe which aspects or dimensions of policies have been emphasized in prior laws. They will discern how the politics played out in these earlier states—which groups were satisfied, which were not; whether there was public support or not; and so on. And they will see what approaches these other states have taken, whether these approaches were successful, whether these approaches would be a good fit in their own states, and whether these adoptions have implications for their states. In other words, they will observe the politics and policy implications surrounding earlier adoptions. They can then use this information to try to define the issue in a specific way in their own state, since, as we have established, these definitions have implications for later stages of the policy process, they are malleable, and they can change over time.

Much of the preceding discussion gets at the notion of learning, and we will return to that momentarily. Before doing so, however, we first address a more basic and essential question: If political actors within a state look to other states when deciding whether and how to define a specific policy problem, which states do they look to? That is, do interdependencies exist within a subset of states, rather than all states?

In the past, scholars have attempted to capture the idea that states are not likely to be in-

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<sup>6</sup>From the analyst's perspective, "[i]n specifying issue-frames, one can aggregate or disaggregate subframes" (Gamson et al., 1992, 385).

influenced by all other states by focusing on factors such as geography (e.g., whether states are influenced by adoptions in geographically contiguous states) or other similarities (e.g., whether states are influenced by adoptions in states that share non-geographic similarities, such as ideology or partisanship). In a recent innovative study, however, [Desmarais et al. \(2015\)](#) provided a new way for scholars to identify where interdependencies exist by developing and applying an algorithm that identifies the underlying network of states within which policies will diffuse. Building on their approach, which we discuss in more detail in Section 3.4, we expect that if issue definition is influenced by prior adoptions, this influence should occur within a state's network, which identifies the states whose policy adoptions typically lead to similar adoptions in a given state. Our first expectation states this relationship:

1. *Diffusion*: Prior adoptions by other states within that state's diffusion network predict the prevalence of policy frames within a state.

This first expectation, although broad, is crucial, as it allows us to determine whether the posited connection between earlier adoptions and later issue definitions exists. Establishing this connection, regardless of whether the relationship is positive or negative, would provide a new way of thinking about diffusion, for the reasons laid out above. We also can build upon it by delving more deeply into the question of why diffusion from adoptions to definitions might occur. To do so we turn to a central theoretical concept within the study of diffusion: that there are several key mechanisms that facilitate diffusion ([Simmons et al., 2006](#); [Braun and Gilardi, 2006](#); [Shipan and Volden, 2008](#)). Briefly, scholars have identified four main mechanisms that explain how policies diffuse: *learning* means that policy makers pay attention to the consequences of policies in other units; *competition* highlights that policy makers adjust their policies to those of other units aiming to attract the same resources; *emulation* (sometimes called *imitation*) focuses on the socially-constructed aspects of policies, whereby their legitimacy, and therefore likelihood of adoption, increases with their spread; and *coercion* emphasizes various forms of top-down influences such as conditionality procedures set by international organizations.

Here we focus on two of these mechanisms: learning and emulation.<sup>7</sup> Much of our earlier

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<sup>7</sup>Coercion generally does not occur in this policy context, although see [McCann et al. \(2015\)](#) for a discussion of



discussion about what political actors would observe from policy adoptions in earlier states can be interpreted as learning. They might, for example, learn about the politics of how a policy played out in other states (e.g., which groups were happy with the adoptions, which were not; whether public reaction was positive; whether the issue affected electoral outcomes; etc.). And they might also learn about policy implications, such as whether the policy worked, who it benefited, and more.

If the connection between earlier adoptions and later issue definitions is based on learning about the practical consequences of adoption, then we would expect to see specific changes in how issues are defined over time. In particular, there are several dimensions of anti-smoking policies where learning about consequences is likely to take place—most notably, those that are practical or concrete enough for consequences to be observed with relative ease. The effect of these laws on bars and restaurants, and on casinos, are cases in point: one can fairly easily assess evidence on whether these businesses struggle or thrive in the aftermath of smoking bans. If states learn from earlier adoptions, then we would expect these particular topics or frames to be related to earlier adoptions, as the frequency of the topic will change based on the learning that has occurred from earlier adoptions.<sup>8</sup> Political actors will learn about the consequences of earlier adoptions, and this knowledge will be reflected by the frequency of a topic changing as a result of earlier adoptions. We state this expectation as follows:

2. *Learning*: Prior adoptions within a state’s diffusion network predict the prevalence of policy frames that are based on practical, empirically verifiable consequences.

States also can emulate actions taken by other states. In a diffusion context, this concept incorporates the idea that when one state emulates another, it does so because the action is normatively appealing—potentially because of a goal of wanting to be perceived like that earlier adopter, or because these socially-constructed aspects of policies are viewed as appropriate, have

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how policy ideas can move “top-down.” We leave this possibility for future study. We also leave the investigation of economic competition to future research, due to a combination of the limited space in this paper (and the already large number of topics we explore) and the lack of a clear theoretical angle on how adoptions would affect framing through diffusion.

<sup>8</sup>The direction of this change will depend on the nature of the topics that emerge from our empirical analysis.

broad support, and confer legitimacy upon the adopter (Walker, 1969; Meyer and Rowan, 1977). This stands in contrast to the learning that can occur about empirically-observable effects, or consequences, of policies. Central to this view is the argument, developed by Finnemore and Sikkink (1998), that when a normatively-appealing idea becomes common and widely accepted, it also becomes internalized by political actors. And when that happens, this idea becomes progressively taken for granted, at which point it is “no longer a matter of broad public debate” (Finnemore and Sikkink, 1998, 895). As a result, we would expect it to fade from view, being invoked with less frequency as a prominent frame as more states adopt policies.

In the area of anti-smoking laws, two such normative frames stand out: freedom and health. Neither are topics where learning will take place—states do not, for example, learn about whether more freedom or more individual rights is a good thing by observing earlier adoptions, and the health consequences of smoking were already well established during the period we examine. Rather, these views are progressively internalized, and debate will take place over other aspects of the policy instead. By this “taken-for-granted” logic, we expect the frequency of these frames to decrease over time as more states adopt policies. Our third expectation highlights this relationship:

3. *Emulation*: There is a negative correlation between policy adoption within a state’s diffusion network and the prevalence of policy frames that are based on normative arguments.

In addition to these three main expectations, we also examine another one. As we have stated, we view individual topics as building blocks, which can either stand on their own as simple frames (or subframes) or can combine to create more complex frames. Hence, a general expectation is that individual frames will combine, with some individual frames occurring in conjunction with others to form more complex frames. At this stage, without having conducted the analysis that will reveal which frames exist, we obviously cannot specify which frames will combine with which other frames. But given the theoretical literature that argues that individual frames can be aggregated (e.g., Gamson et al., 1992), we expect to find that at least some frames will occur together, and that their co-occurrence may be related to policy adoption within a state’s diffusion network.

## 3 Methodology

### 3.1 Case selection

Our analysis of policy frames as a part of the diffusion process concentrates on the adoption of antismoking policies in US states. US states historically have had considerable autonomy in the area of public health, and smoking restrictions are no exception. Although smoking-related issues are often discussed by politicians at the national level (McCann et al., 2015), few laws have been passed at this level in the US; rather, the vast majority of policymaking has taken place within the states. Thus, the issue of anti-smoking laws at the state level provides an excellent forum for examining the process of diffusion.

Our choice of policy area is also motivated by several other considerations. First, several studies (Studlar, 1999; Shipan and Volden, 2006, 2008; Rogers and Peterson, 2008; Pacheco, 2012), along with abundant anecdotal evidence, indicate that smoking ban adoptions have exhibited a diffusion process. This allows us to concentrate on the nature of the process—in particular, the ways in which this issue has been defined—rather than the mere existence of the diffusion of adoptions. Second, smoking bans have been adopted in a convenient time frame—roughly a fifteen-year period—that is long enough to detect variation and to supply sufficient information, but short enough to be practically manageable. Third, there was significant uncertainty about the potential consequences of the policies along a number of dimensions, including economic consequences, popular support, interest group support, ease of implementation, and so on (Jacobson et al., 1997). Finally, this uncertainty over consequences means that the debate over adoption can be framed in multiple ways.

### 3.2 Corpus

The construction of the corpus is discussed in detail in Appendix A. Briefly, we retrieved and processed articles published in 49 newspapers in the US covering 49 states between 1996 (two years before the first statewide smoking ban was adopted in California) and 2013. We use print media rather than television or radio programs partly for technical reasons but especially be-

cause they report more extensively on political matters than do on-air media (Druckman, 2005, 469). Moreover, the newspaper market in the US in general is regionally structured, with a majority of newspapers focusing on political news in their state (Graber and Dunaway, 2015). We therefore can expect newspapers to convey rich information on local debates on smoking bans. One question that arises is whether the media coverage we examine reflects how policies are framed, or whether it influences the frames. On this question we are agnostic. Regardless of whether this coverage reflects or influences frames, media coverage can be used as an accurate source for identifying the ways in which smoking bans are framed and, more generally, as an indicator of how they are discussed (Baumgartner et al., 2008).<sup>9</sup> We retrieved newspaper texts using a simple, broad keyword search from different database providers. To remove irrelevant paragraphs, we conducted a supervised text classification based on crowd-annotation (Benoit et al., 2016) and a machine-learning classifier. The final corpus consists of 52,675 paragraphs.

### 3.3 Structural Topic Model

We identify policy frames inductively with a structural topic model (STM) (Roberts et al., 2014b, 2016). The STM builds on well-established generative topic models, namely the Correlated Topic Model (CTM) (Blei and Lafferty, 2007), which is itself an extension of the well-known Latent Dirichlet Allocation model (LDA) (Blei et al., 2003). The STM’s major innovation is that the prior distribution of topics can vary as a function of covariates (Roberts et al., 2014b, 2016). The inclusion of covariates in the topic model makes it possible to assess relationships among variables in a regression-like framework, that is, to uncover covariation between topic prevalence and variables of interest. Concretely, in our study, the STM’s ability to include covariates means that we can directly examine our expectation that topic prevalence within a state—which is our measure of issue definition—is linked to prior policy adoptions by other states within that state’s diffusion network. Moreover, the STM allows us to control for other factors that might be related to topic prevalence. We discuss the covariates that we include in our analysis in Section 3.4.

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<sup>9</sup>We emphasize that we are *not* examining whether newspaper editors learn, or are part of the diffusion process. Rather, because newspaper accounts indicate how issues are framed and discussed, we can use them to capture this information and thus to provide insights into diffusion from adoptions to frames.

We estimate our topic models using the `stm` package in R (Roberts et al., 2014a). We initialize the models with the spectral algorithm, which is robust to changes in several CTM parameters and starting values (Roberts et al., 2016). We evaluated 47 models using `word2vec` (O’Callaghan et al., 2015), varying the number of topics from 3 to 50, and found that models with relatively few topics performed better (see Appendix B.1 for details). After a qualitative evaluation of the most-probable words<sup>10</sup> and documents of the models’ topics in this range, we selected the 12-topic model as the most useful for our analysis. However, the results of models assuming 3 to 13 topics show that the models identify the same underlying topics, although obviously with different degrees of granularity.

The STM model also allows us to retrieve estimates of correlations between topics. In other words, it lets us see how the prevalence of the various topics co-vary. We will focus only on positive correlations, for several reasons. First, in mixed-membership models such as STM the topics inherently crowd each other out, since their prevalence must sum up to 1. Second, our strategy to select the optimal number of topics pushes topic correlations in the negative direction because we wanted topics to pick up words that are maximally exclusive, that is, that separate topics neatly (see Appendix B.1). Consequently, most correlations will be negative and those correlations that are positive will not be very strong. However, precisely because our approach is biased against positive correlations, those we do find can be interpreted as substantial.

### 3.4 Covariates

The most important covariate in our analysis measures the *share of prior policy adoptions within a state’s diffusion network*. The construction of this variable mirrors that of a spatial lag, which is a weighted average of the policies of other states (Plümper and Neumayer, 2016) and is the key variable of interest in most diffusion studies. To construct this spatial lag, we need two pieces of information. First, we need to know when various types of smoking bans were enacted in each state. Following Shipan and Volden (2006), we purchased these data from MayaTech’s Center for

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<sup>10</sup>The probability of observing each word in the vocabulary under a given topic, or  $\beta$ , is one of the main outputs of the STM (Roberts et al., 2016). For the most-probable word lists per topic, words are ranked according to their topic-specific probability.

Health Policy and Legislative Analysis. We consider smoking bans in seven areas: restaurants, bars, government worksites, private worksites, hotels, malls, and indoor arenas.

Second, we need a connectivity matrix containing information on the relationship between states; specifically, which states are likely to influence each other. Traditionally, the literature has relied on simple geographic proximity, a catch-all indicator that is theoretically blunt (Maggetti and Gilardi, 2016). Instead, we use the dataset constructed by Desmarais et al. (2015), which identifies a latent, dynamic policy diffusion network for US states that goes beyond mere geographic proximity. Concretely, this approach identifies the likelihood that state  $i$  is identified as a policy source for state  $j$  based on three pieces of information: the frequency with which  $i$  adopts a policy before  $j$ ; the time lag between  $i$ 's and  $j$ 's policy adoptions; and the accuracy with which a policy adoption by  $i$  predicts a policy adoption by  $j$ . Applying a latent network inference algorithm to the adoption of 187 policies over 49 years, these authors “infer an evolving state-to-state policy diffusion network for the years 1960–2009” (Desmarais et al., 2015, 395). That is, they estimate, for each year, which pairs of states are connected by “diffusion ties.” For each pair of states, they estimate whether policies diffuse from one to the other, and in which direction. The result is a directed dyadic dataset that easily can be used to construct a binary connectivity matrix, similar to a traditional geographic contiguity matrix, but reflecting the latent policy diffusion network much more accurately than geography does.<sup>11</sup>

The analysis includes several other covariates, which we use to control for relevant factors that might affect the way smoking bans are framed: (1) a monthly trend variable (with a B-spline of order 10), to control for the baseline trend of topics' proportions; (2) newspaper IDs, to identify the states in which newspapers are based; (3) newspapers' ideological “slant” (Gentzkow and Shapiro, 2010), since a newspaper's ideological leaning might affect its coverage of smoking bans; (4) the percentage of smokers in the state where the newspaper is based, since this might be related to the popularity of smoking bans; (5) whether a newspaper is based in a tobacco-

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<sup>11</sup>Desmarais et al. (2015) show that diffusion occurs most commonly across states that are *not* contiguous. Since the diffusion network data are available only until 2009, we predicted the remaining years (2010–2013) using temporal exponential-family random graph models, whose forecasts were trained and evaluated with data for the 14 years available in Desmarais et al. (2015). We discuss this procedure, which was designed and implemented by Fridolin Linder, in Appendix C.

producing state (for the same reason); (6) whether Democrats or Republicans form a unified government in a state, because the two parties tend to have different views about smoking restrictions; (7) the presence of smoking bans in a state; (8) the number of months before and after the enactment of smoking bans (with a B-spline of order 10), since the framing of smoking bans is likely to change before and after their introduction; and (9) the sentiment of a given paragraph, which we measured with the same approach we used for the identification of relevant paragraphs (see Appendices A.3 and A.4).<sup>12</sup>

## 4 Results

The discussion of our results proceeds in two steps. First, in Section 4.1 we present the topics identified by our STM and their distribution over time. Second, and most importantly, in Section 4.2 we evaluate our expectations about how these topics, or frames, are related to policy diffusion—that is, whether and how prior adoptions within a state’s diffusion network predicts topic prevalence and how individual topics connect with one another to form broader frames.

### 4.1 Topics

For the reasons explained in Section 3.3, we present the results of a model assuming 12 topics.<sup>13</sup> A detailed validation is discussed in Appendix B.2, and other appendices provide further details.<sup>14</sup> We determined the label for each topic based on the top fifty words for each topic, as well as a reading of the most relevant paragraphs for each topic. The topics are sorted by decreasing average prevalence. In addition, we group the twelve topics into six categories, based on how they are correlated with one another (as discussed in sections 3.3 and 4.2): *Normative*, which in-

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<sup>12</sup>We defined a paragraph as “pro” smoking bans if it reports facts or opinions that emphasize the need for, or success of, smoking restrictions. Conversely, we defined a paragraph to be “anti” smoking bans if it conveys facts or opinions that highlight potential problems associated with smoking restrictions.

<sup>13</sup>The confidence intervals “incorporate estimation uncertainty of the topic proportions into the uncertainty estimates using the method of composition,” which is the most conservative procedure available in the `stm` package (Roberts et al., 2014a, 14).

<sup>14</sup>Appendix B.3 shows the top fifty words associated with each topic. Appendix B.4 shows the distribution of the prevalence of these topics over time, as well as each topic’s average prevalence over the observation period. Appendix B.5 shows examples of the most relevant paragraphs.

cludes *Freedom* and *Health*; Regulations, which includes *Bars and restaurants*, *Local legislation*, *Regulations*, and *Enforcement*; Casino legislation, which includes both *Casinos* and *State legislation*; Spaces, which includes *Schools and universities* and *Outdoors*; and two other categories, Interest Groups and Politics, which consist of one topic each (*Tobacco companies* and *Electoral politics*, respectively). The model does an excellent job of identifying relevant topics that are clearly connected with smoking bans and are consistent with those found by public-health experts who hand-coded documents (e.g., [Menashe and Siegel, 1998](#); [Magzamen et al., 2001](#)).

## 4.2 Assessing Our Expectations

### Diffusion

We begin with our first expectation, which is that issue definitions within a state are predicted by prior adoptions of smoking bans by other states within that state's diffusion network. In other words, we expect that the way an issue is defined (or framed) within a state is predicted by the presence or absence of adoptions within that state's diffusion network. We can assess this by plotting the prevalence of a frame against the proportion of prior adoptions within a state's network, to see whether the prevalence co-varies with earlier adoptions or is unrelated to these adoptions.

Figure 1 presents plots of issue definition versus prior adoptions for each of our topics. It provides direct evidence of this phenomenon, indicating that the prevalence of some topics is indeed predicted by prior policy adoptions within the diffusion network. *Regulations*, *Bars and restaurants*, *Local legislation*, and *Tobacco companies* all show a pattern of decreasing prevalence as the proportion of adoptions increases. Meanwhile, *Enforcement*, *Casinos*, *Electoral politics*, *Outdoors*, and to some extent *State legislation* show the opposite effect, with these frames becoming more prevalent as more states within the network adopt bans. Not all topics, however, vary in prevalence with respect to the share of prior adoptions. In particular, *Health*, and *Freedom* show no covariation with prior adoptions, a finding we return to below.

The plots thus provide evidence consistent with our first expectation about diffusion, show-



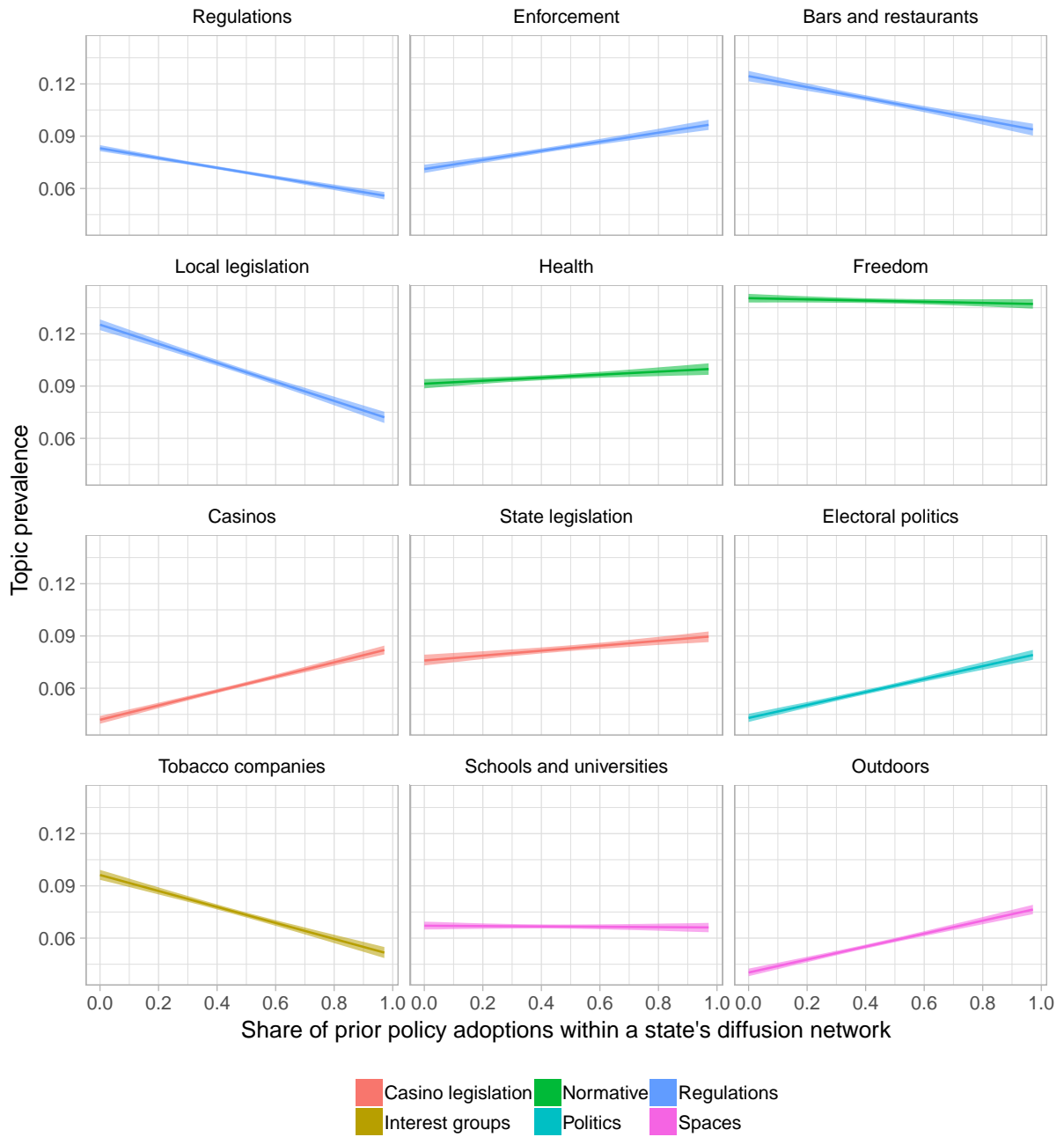


Figure 1: *Topic prevalence co-varies with the share of prior policy adoptions within a state's diffusion network.*

ing that many, although not all, topics are predicted by levels of prior adoptions. We now turn to our second and third expectations, both of which are based on the mechanisms of diffusion.

## **Learning**

Our second expectation (*Learning*) implies that there are some topics where learning can take place, where earlier claims about a policy and its effects can be empirically verified (or not), and that this will be reflected in the frequency with which a topic is raised in other states.

Several of the plots in Figure 1 provide support for these conjectures. We begin by focusing on topics that fall within the category of *Regulations*, which includes topics related to concrete aspects of smoking bans. We find that the correlation between prevalence and prior adoptions is strong—and negative—for *Bars and restaurants*, indicating that the prevalence of this topic decreases as a higher proportion of the other states within a state’s diffusion network adopt anti-smoking laws. Opponents of smoking restrictions regularly raised concerns about the potential harmful economic effects of such policies on bars and restaurants. When these predictions of harm were not borne out (Warner, 2000; Tomlin, 2009), this frame faded.

A negative correlation is also exhibited for the *Regulations* topic within this category. This topic identifies the technical aspects of smoking bans, such as rules or permits for separate smoking areas, ventilation, and exemptions. Getting these regulations right is important for the implementation of bans, as uncertainty surrounding them may worry business owners. Figure 1 shows a negative correlation between *Regulations* and prior adoptions within the network, indicating that these issues are quite salient when no other state within the diffusion network has enacted smoking bans, and less so when many have. This finding suggests that the experiences of other states are used to update beliefs—in this case, what kind of regulations work best or how difficult it is to get them right.

A similar interpretation can be made for *Enforcement*, another practical aspect of smoking bans in the same category. The salience of this topic increases as more evidence from states within the diffusion network becomes available, showing that the enforcement of smoking bans is not always unproblematic. The last correlation in this category, that for *Local legislation*, is

also negative. This finding suggests that the decision-making process may shift from the local to the state level when state legislation becomes more widespread within the diffusion network.

We also find evidence for our learning expectation in other categories. Consider our *Casinos* category, which refers to state legislation introducing smoking restrictions in casinos. The specific *Casinos* topic within this category becomes more salient when many states within the diffusion network enact smoking bans, suggesting that their experience points to negative consequences for the casino business. Indeed, studies of the economic effects of smoking restrictions on casinos often have concluded that such laws have been harmful to casinos (e.g., [Garrett and Pakko, 2010](#); [Thalheimer and Ali, 2008](#)). As more states adopt laws, and as evidence begins to amass that points to potential harmful consequences, learning occurs and the topic is more likely to emerge as a frame.

Next, our findings for topics in the *Politics* and *Interest groups* categories indicate that states can learn not only from policy outcomes in other states within their diffusion network; they also can learn about political outcomes. *Electoral politics* identifies voters' involvement in the decision-making process, and more generally the political-electoral dimension of smoking ban adoption and implementation. It becomes a much more prominent topic when states within the diffusion network start to pass smoking restrictions. Figure 1 also shows that another prominent political dimension, that of the dominant interest organization in this area—*Tobacco companies*—is strongly and negatively correlated with policies within the diffusion network. That is, as more states within the diffusion network adopt these restrictions or bans, *Tobacco companies* is less likely to emerge as a topic or frame. Given that restrictions and bans are usually adopted over the opposition of this industry, and given the growing distrust of these companies during the period we examine, the increasing success of other states within the diffusion network in adopting such policies means that states may no longer see tobacco companies as pivotal actors and consequently see less need to focus on or defer to them.

## Emulation

Our emulation expectation states that for topics that are widely shared and internalized we would expect a decrease in attention as more and more states adopt policies. The reason for this drop-off is that these aspects of a policy will become widely accepted, even taken for granted. And when this happens, they will fade from public discourse.

To examine this expectation, we consider the category of *Normative*. Topics in this group are not linked to concrete, empirically verifiable aspects of smoking bans. Rather, they refer to the main rationales for supporting or opposing smoking bans. The usefulness of smoking bans to improve health, and their compatibility with individual freedom, are arguments that potentially can become taken for granted and achieve a status in which they are, to again quote [Finnemore and Sikkink \(1998, 895\)](#), “no longer a matter of broad public debate.” Therefore we expect a negative correlation between normative topics and previous adoptions within a state’s network.

Contrary to this expectation, [Figure 1](#) shows that topics in the *Normative* group are not correlated with the policies of other states. In particular, *Freedom* is discussed with about the same frequency regardless of how many states within the diffusion network have enacted smoking bans. The compatibility of smoking bans with individual rights is highly salient in public debates on smoking bans—indeed, it is the most frequent topic (see [Figure B7](#) in the Appendix)—but its relevance does not increase or decrease, relative to other topics, when more states within the diffusion network adopt the policy. That is, the experiences of other states do not change the frequency—again, relative to other topics—with which smoking bans are discussed in connection with individual rights, implying that *Freedom* is not an important dimension of the diffusion of smoking bans. The *Health* frame also shows very little change corresponding to the number of earlier adoptions (and unlike *Freedom*, it increases very slightly). Perhaps this lack of correlation between prior adoptions and topic prevalence is because these normative dimensions are tied tightly to any consideration of these policy areas, and spread from place to place. Whatever the specific cause, the findings for *Freedom* and *Health* run contrary to our expectation about emulation.

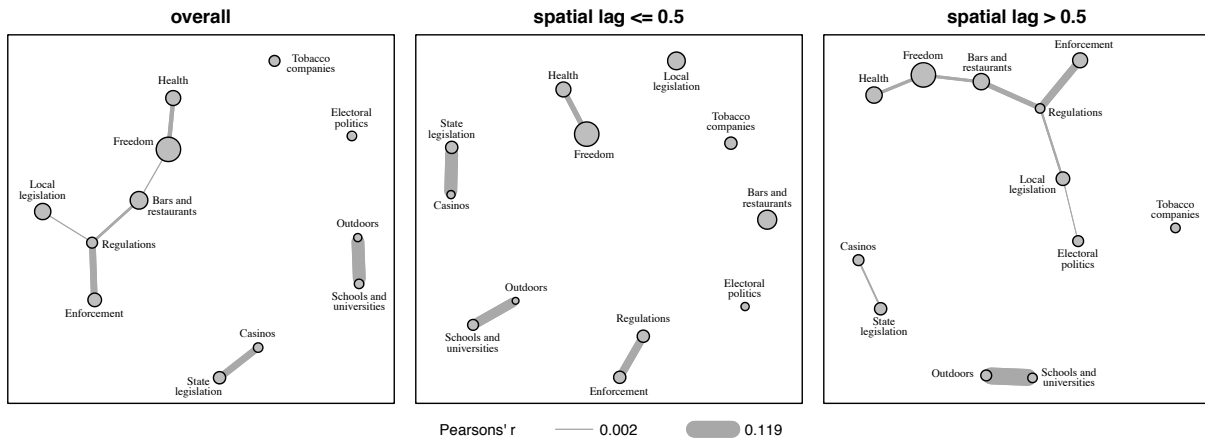


Figure 2: *Topic correlations over all paragraphs (left panel) and as a function of a low (center panel) or high values (right panel) of the spatial lag, that is, the share of prior policy adoptions within a state’s diffusion network. Correlations are calculated by taking Pearson’s  $r$  over two topics’ prevalence in all paragraphs. The thickness of the edges is proportional to the strength of the correlation while the size of the size of the nodes is proportional to prevalence of the topic. Only positive correlations shown.*

### Topic Correlations

We now turn to our expectation about the connections between individual topics. In examining correlations between topics, we consider both their nature and how they co-vary with the share of prior policy adoptions within a state’s diffusion network. Figure 2 shows, in network format, how our individual topics correlate with one another. For the reasons explained in Section 3.3, we focus only on positive correlations. The left panel of Figure 2 shows correlations computed using the whole corpus, and is the basis for the categories we have used so far. The middle panel computes correlations using the subset of texts for which the values of the spatial lag is smaller than or equal to 0.5—that is, cases in which fewer than 50% of states within the diffusion network have adopted the policy. Finally, the right panel shows the correlations when most states within the network have adopted the policy.

The main pattern that emerges from Figure 2 is that topics tend to be more closely linked with one another when more states within the diffusion network adopt the policy. In other words, policy frames tend to become more complex as the policy diffuses. When few states within the diffusion network have adopted the policy (i.e., the middle panel), *Regulations* and *Enforcement*

tend to be discussed together, but not in conjunction with other topics. The same holds for *Health* and *Freedom*. Moreover, several topics are discussed in isolation. However, when many states within the diffusion network have adopted the policy, we see the emergence of a broad frame connecting many topics. The central node of this frame is *Regulations*, with connections not only with *Enforcement*, but also with *Health* and *Freedom*, via *Bars and restaurants*, as well as *Electoral politics*, via *Local legislation*. That is, a much more complex frame emerges, combining practical, normative, and political aspects. This evidence suggests that policy diffusion is associated with policy frames taking more sides of the problem into account.

### 4.3 Summary

We conclude that the way smoking bans are framed is predicted by the prevalence of the policy within a state's diffusion network, which supports our first expectation (*Diffusion*). As the policy becomes more widespread, some issues (such as the consequences of smoking bans for casinos, enforcement problems, and political support for the policy) gain salience and prominence, while others (e.g., the consequences for bars and restaurants, the influence of tobacco companies, and regulatory details) become less relevant. Notably, and consistent with our second expectation (*Learning*), these topics refer to the practical, observable consequences of smoking bans. On the other hand, topics that capture normative aspects of the debates over this policy area are unaffected by earlier adoptions, which goes against our third expectation (*Emulation*). Finally, the complexity of policy frames increases with diffusion. As the policy becomes more widespread, policy frames take into account more aspects of the problem, connecting previously separate topics linked to the normative, practical, and political implications of smoking bans.

## 5 Conclusion

Our study brings a new perspective to the study of policy diffusion by focusing on framing and issue definition. Rather than examining whether policy adoptions are a function of previous adoptions, which has been the standard approach, we instead have investigated another aspect of

diffusion, one that has been overlooked and for which there is no existing conventional wisdom. Namely, we investigate the link between these previous adoptions and the way an issue is defined or framed.

Our analysis shows that issue definition is an integral part of the diffusion process (and similarly that diffusion plays a key role in issue definition). Most notably, we find that as a policy becomes more widespread within the diffusion network, the ways an issue is defined changes, although this connection does not exist for all types of frames. Normative rationales of a policy are relatively unrelated to previous adoptions. On the other hand, more practical aspects in which learning can occur are defined differently when most peer states have adopted the policy than when few have, with some frames becoming more prevalent as adoptions become more frequent while other frames fade away as the experience of others demonstrates their irrelevance. Moreover, frames tend to become more complex as the policy spreads.

Viewed from the perspective of policy diffusion theory, our findings mean that the effects of diffusion come into evidence well before the adoption stage, or even the agenda-setting stage. Policy diffusion can affect policymaking by shaping how issues are defined—that is, by shaping the first stage of the policy process. In other words, the reach of diffusion processes, and their potential to influence policymaking activity, is even larger than currently assumed. Moreover, our findings imply that conventional results, focusing narrowly on policy adoptions, might be somewhat misleading, or potentially even spurious, since diffusion operates prior to the adoption stage.

We also show that there is another benefit to focusing on stages prior to adoption. Explaining whether a policy is adopted, which has been the standard approach in diffusion studies, is certainly valuable. But for this approach to work, the policy under study must be widespread; otherwise the dataset will include too many 0s and too few 1s in the dependent variable for the analysis to be reliable or even feasible. Moreover, policies must be easily measurable and comparable. However, many important policies cannot be easily measured or compared across units; and many phenomena may not (yet) be widespread. In such cases, a conventional diffusion approach that focuses on adoptions as a dependent variable cannot be used, even though a dif-

fusion perspective—one showing how policymaking activities in previous and current states are related—might be highly relevant. The approach we have used shows how scholars can study any policy or a range of political phenomena from a diffusion angle, regardless of whether policies have been adopted.

Our analysis sets the stage for the examination of an additional set of theoretical and empirical questions, ones that we have not tackled here either due to reasons of space or because our current approach does not allow for it, but questions that would not have been apparent before our analysis. One such question concerns the direct link between policy frames in earlier states and policy frames in later states. Such frame-to-frame diffusion cannot be studied within our framework, because the STM estimates the prevalence of topics and their correlations with covariates (e.g., the frequency of prior adoptions) simultaneously. Thus, while we can include prior adoptions as covariates, we cannot include the prevalence of earlier frames within a state's network as a covariate in the STM, because this prevalence is unknown prior to estimating the model. A study that builds on our paper and examines the link between frames in different states would be a highly illuminating addition to the diffusion literature. Similarly, future studies should work to develop new ways to assess the link between sentiment and framing as a measure of issue definition. Combining topics and sentiment in a coherent outcome variable is difficult within our methodological approach, because although we included sentiment as a covariate, measured prior to the analysis, topics are identified inductively together with their correlation with covariates. Finally, future research should attempt to go beyond prediction to measure causal effects. It is a daunting task in this context because it requires solving simultaneously two hard problems that the literature is just starting to address taken individually (but not yet in conjunction), namely, causal inference with text data (Egami et al., 2018) and the identification of causal diffusion effects using observational data (Egami, 2018).

While acknowledging the relevance and importance of these other questions and topics, it is worth emphasizing that they arise because of the work we have done in this paper. Until now, there has been no investigation of the connection between prior adoptions and the beginning steps of the policy process (i.e., issue definition and policy frames) in later states. The primary



value of our approach is that it provides a new and innovative way to investigate this connection. On its own, this constitutes a valuable addition to the literature on policy diffusion. But it also provides a foundation that other studies can build on to explore new avenues that will further enrich our understanding of diffusion and the policy process.

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# Appendix

# A Corpus

## A.1 Corpus description

The time period we examine begins in 1996, which is two years before California adopted the first statewide smoking ban.<sup>15</sup> To analyze public discussions and identify policy frames within a state, we processed articles published in 49 newspapers in the US covering 49 states (see Table A.1). Our goal was to include one newspaper for each state. Accordingly, our corpus includes the largest newspaper in terms of circulation in each state (or one of the largest, depending on availability). The corpus covers the full period for most newspapers.

We retrieved newspaper texts using a simple, broad keyword search from different database providers. Then we split the texts into paragraphs of similar length and removed duplicate paragraphs, which produced a corpus containing 3,159,350 paragraphs. We provide more details on these procedures in Section A.2. A manual evaluation of a random sample of paragraphs revealed a very low share of paragraphs actually covering smoking bans, most likely due to the looseness of our keyword search, which was aimed at minimizing the number of articles on smoking bans escaping our search. To remove irrelevant paragraphs, we conducted a supervised text classification. First, we used the crowd-sourcing platform Crowdfunder to annotate a sample of about 10,000 paragraphs as relevant or irrelevant. We followed the procedures in Benoit et al. (2016) and found that the crowd annotation produced results comparable with three expert codings. In Section A.3 we discuss the coding instructions given to the crowd-workers and the validity of the crowd-coding.

Second, using the information obtained through crowd annotation, we then classified all paragraphs in our corpus as relevant or irrelevant using a machine-learning classifier built with the Python module `scikit-learn`. Prior to the classification, we pre-processed all documents with standard procedures.<sup>16</sup> Next we evaluated seven algorithms<sup>17</sup> on 100 bootstrapped training samples and optimized the output in terms of the ratio between true positives and false positives (i.e., the receiver operating characteristic). The support vector machine proved to be the most effective classifier, outperforming all other algorithms as well as any ensemble of the seven classifiers. As discussed in Section A.4, the support vector classifier worked well, producing a final corpus of 52,675 paragraphs.

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<sup>15</sup>Debates on smoking bans go back at least to the introduction of the first smoke-free spaces in the 1980s. There were occasional acts before then, such as the Minnesota Clean Indoor Air Act, which called for a partial smoking ban in bars and restaurants as early as 1975. However, our analysis requires significant public debates associated with highly visible events.

<sup>16</sup>Text segmentation, tokenizing, removal of punctuation, collapsing of  $n$ -word geographical names such as “New York” to one token (“New\_York”), lemmatizing, part-of-speech tagging, and conversion of all words to lowercase.

<sup>17</sup>Ada boost, Bernoulli naïve Bayes, Gaussian naïve Bayes, K-nearest neighbors vote, random forest, support vector machines, and logistic regression.



<i>Newspaper</i>	<i>State</i>	<i>Articles</i>	<i>Paragraphs</i>	<i>Filtered</i>
Albuquerque Journal	NM	4,953	25,464	849
Argus Leader	SD	3,801	25,339	1,150
Arizona Republic	AZ	9,405	44,455	2,013
Atlanta Journal-Constitution	GA	23,281	114,843	1,486
Austin American-Statesman	TX	12,573	86,686	1,033
Baltimore Sun	MD	14,264	86,647	1,621
Billings Gazette	MT	235	1,416	92
Birmingham News <sup>a</sup>	AL	1,914	9,000	12
Bismarck Tribune	ND	10,251	40,867	1,411
Boston Globe	MA	19,337	112,465	2,257
Burlington Free Press	VT	1,938	10,607	407
Charleston Gazette-Mail	WV	18,228	116,099	1,832
Chicago Tribune	IL	31,855	157,102	3,183
Clarion-Ledger	MS	3,206	17,005	443
Courier-Journal	KY	10,593	7,1887	2,752
Daily News	NY	14,202	60,828	777
Dayton Daily News	OH	9,767	45,444	784
Democrat-Gazette <sup>a</sup>	AR	4,678	16,422	76
Denver Post	CO	13,088	79,843	1,292
Des Moines Register	IA	5,750	41,160	857
Deseret News	UT	15,884	58,817	879
Detroit Free Press	MI	11,309	115,380	761
Hartford Courant	CT	14,821	83,980	731
Honolulu Star-Advertiser	HI	1,465	8,282	180
Idaho Falls Post Register	ID	2,082	11,083	95
Indianapolis Star	IN	11,432	92,001	2,346
Journal Sentinel	WI	16,040	81,146	1,005
Las Vegas Review-Journal	NV	9,430	56,605	1,135
Los Angeles Times	CA	29,597	196,061	1,881
News Journal	DE	5,426	31,177	1,220
North Jersey Record	NJ	19,453	95,395	1,368
Oklahoman	OK	12,250	44,793	1,093
Omaha World-Herald	NE	12,295	72,506	1,711
Oregonian <sup>a</sup>	OR	3,406	17,154	141
Philadelphia Inquirer	PA	18,975	105,861	1,374
Portland Press Herald	ME	5,374	27,796	718
Post and Courier <sup>a,b</sup>	SC	13859	28362	7
Providence Journal	RI	15,264	89,549	1,349
Richmond Times-Dispatch	VA	23,237	141,295	923
Seattle Times	WA	16,820	79,862	910
St.Louis Post-Dispatch	MI	27,516	137,830	2,821
Star Tribune	MN	13,693	120,220	1,840
Tampa Bay Times	FL	22,369	162,254	1,271
Tennessean	TN	5,475	36,611	608
Times-Picayune <sup>a</sup>	LA	3,600	17,776	90
Topeka Capital-Journal	KS	5,976	32294	564
Union Leader <sup>a</sup>	NH	975	3,944	43
Wilmington Star-News	NC	6,863	34,211	515
Wyoming Tribune Eagle	WY	2,024	13,526	769
<b>Total</b>		<b>560,229</b>	<b>3,159,350</b>	<b>52,675</b>

<sup>a</sup> Several years of coverage could not be retrieved due to access restrictions.

<sup>b</sup> Documents retrieved with a simplified keyword search string, since it was only available in one specific database.

Table A1: *Newspaper corpus.*

## A.2 Newspaper articles retrieval and preprocessing

The keyword string for the different newspaper databases was an adaptation of “tobacco OR non-smoking OR anti-smoking OR smoking OR cigar! OR (lung AND cancer) OR smoker.” The specific form of the keyword string depends on the options available for Boolean operators and truncation wildcards.

We then split the texts into paragraphs of a similar length. The original paragraph structure of the documents was kept, but paragraphs with fewer than 150 tokens were merged until the paragraph exceeded 150 tokens. This ensures the comparability of the texts from different newspapers and across different document formats in each newspaper.

Following many previous newspaper text analyses in political science (e.g., [Hurrelmann et al., 2009](#); [Wueest et al., 2011](#)), we disaggregate the retrieved newspaper articles into single paragraphs. We did so for two reasons. First, newspaper articles have very different lengths. Brief news stories and lengthy background reports occur even within the same newspaper. By splitting articles into paragraphs, we construct a more balanced corpus. Second, in journalistic writings, paragraphs usually are the basic structuring elements that feature a coherent and distinct content, and not all content is relevant for our topic. Our corpus, for example, contains a lot of general reports on parliamentary sessions. The debate on smoking bans is often only one among many debates that are covered in the same news article. Therefore, for our purposes the texts covering such other debates are best discarded for the analysis, as they would just introduce noise.

Finally, we identified and removed duplicate paragraphs. Our downloads contained a considerable number of articles that are almost duplicates of other articles—about 3 to 20 percent, depending on the newspaper outlet. These almost-duplicates are generated because publishers upload different versions of the same article into the database (e.g., when small corrections are made). We found that two paragraphs with a Jaccard distance of 0.97 or higher on their word sets can be safely classified as duplicates and we kept only one of them.

## A.3 Evaluation of crowd coding

Our coding instructions indicated that relevant paragraphs are those containing information on smoking restrictions—that is, bans or limits on smoking in public places or specific workplaces. This definition includes statements about any kind of restriction of smoking (“smoking ban”) in public places or businesses introduced through legislative action, executive action, or other democratic actions (e.g., direct-democratic processes). By contrast, we defined paragraphs discussing, for example, smoking bans introduced by private actors (e.g., companies, businesses), or bans of specific tobacco products (e.g., mentholated cigarettes), as irrelevant.

For establishing a development set for the classification of paragraphs into relevant or irrel-

average crowd coder judgement	N evaluated as relevant	N evaluated as not relevant	N overall
0	–	6,930	6,930
0.2	–	1,688	1,688
0.4	31	450	481
0.6	98	118	216
0.8	168	40	208
1	373	–	373
total	670	9,226	9,896

Table A2: *Evaluation of crowd coding.*

evant ones in terms of coverage of smoking bans, we randomly draw around 10,000 paragraphs from the corpus and let them annotate on the crowd-coding platform Crowdfunder.com as follows. First, we coded a sample of 60 paragraphs to establish the gold standard for the crowd coding. We deliberately oversampled relevant paragraphs to make sure crowd coders have enough learning material for this class. In a random sample, their share would have been negligible (around 7 percent). This gold standard was then used for an entry test as well as the continuous quality control during the annotations—every coder needed to have at least 80 percent of the gold standard questions correct. Otherwise, annotations were dropped. Second, we let five crowd coders annotate every paragraph in the full sample. As the evaluation in the following table shows, coders did fully agree in their judgement on most paragraphs. For average judgements of 0 (all coders agree that a paragraph is irrelevant), 0.2 and 1, we only checked a random sample but found no false judgements. As for the average judgements of 0.4 to 0.8 (a total of 905 paragraphs or 9 percent of the sample), we double-checked every paragraph after the crowd annotation. There are false positives and false negatives, as the second and third column in the table below show, but the crowd annotation generally performs well even if not all coders agree in their judgement.

#### A.4 Evaluation of the support vector classification filter

The support vector classifier worked well. Our evaluation indicates that 82 percent of the paragraphs classified as relevant, and 99 percent of those classified as irrelevant, are also identified as such in the crowd-annotated data. Moreover, the classifier is able to retrieve 85 percent of all paragraphs crowd-coded as relevant, and 99 percent of those crowd-coded as irrelevant. Finally, most classification runs we tested agreed, with an overall F1-Score<sup>18</sup> of 0.80 or higher—a further sign of the consistency and thus reliability of the classification (Collingwood and Wilkerson,

<sup>18</sup>The F1-Score is the harmonic mean of precision and recall. In addition, the overall F1-Score is inversely weighted by the number of documents in each class.

2012).

	Precision	Recall	N held-out set
Irrelevant	0.99	0.99	1,790
Relevant	0.82	0.85	136
Average	0.98	0.98	1,926

Table A3: *Evaluation of the support vector classification filter. Recall is the fraction of correct classifications among the retrieved documents; precision is the fraction of correct classifications that have been retrieved over the sum of correct classifications; the held-out set is a subset of the training data that is exclusively used for evaluating the classifier.*

## B Topic models

### B.1 Topic model coherence and discrimination

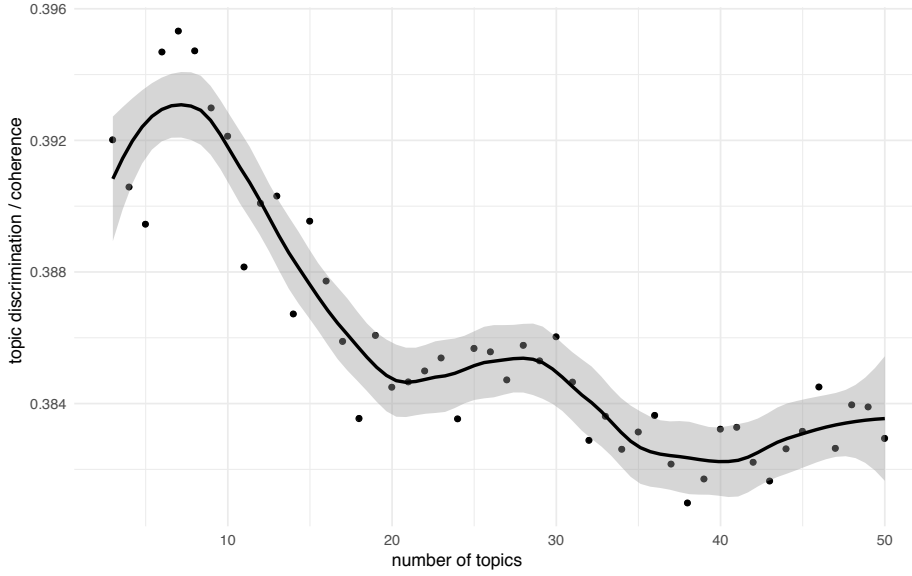


Figure B1: *Word2vec* topic coherence and discrimination averages for varying numbers of topics.

For this evaluation, the word2vec topic coherence and discrimination is calculated as follows. Let  $T = t_1, \dots, t_K$  be the  $K$  topics estimated by a model and  $t_i = [w_{i1}, \dots, w_{iP}]$  a vector of  $P$  top ranked words that characterize each topic. In addition, let  $w_{ij} = [d_{i1}, \dots, d_{iD}]$  be the  $D$  dimensional semantic space estimated by *word2vec* for term  $w_j$  in topic  $i$ . Then, the coherence of topic  $t_i$  is the mean pairwise cosine similarity among the terms in the topic's word vector (see [Greene and Cross, 2017](#)):

$$c(t_i) = \binom{P}{2}^{-1} \sum_{m=2}^P \sum_{n=1}^{m-1} \cos(\theta_{w_{im}, w_{in}}).$$

The discrimination between two topics  $t_i$  and  $t_j$ , in contrast, is the averaged inverse of the pairwise cosine similarity of all word pairs across the topics:

$$d(t_i, t_j) = P^{-2} \sum_{m=1}^P \sum_{n=1}^P (1 - \cos(\theta_{w_{im}, w_{jn}})).$$

Our objective function for the evaluation of the topics, finally, is the average of discrimination and coherence weighted by  $\alpha$ , which is set to 0.3 in our case:

$$f(T) = \alpha \binom{K}{2}^{-1} \sum_{i=2}^K \sum_{j=1}^{i-1} d(t_i, t_j) + (1 - \alpha) K^{-1} \sum_{i=1}^K c(t_i).$$

## B.2 Validation

We validate the output of the model by considering some correlations that help us to assess the plausibility of our results. First, we consider how topics correlate with the timing of smoking ban adoptions at the state level. Figure B3 below shows that the topic *State legislation* is much more prevalent during months in which state legislation was adopted than in other months, which, of course, is exactly what one would expect.<sup>19</sup> Second, Figure B4 looks at the prevalence of topics before and after adoption. This figure shows peaks for several of our topics at the moments one would expect them to be most prominent: *State legislation* and *Electoral politics* during the month of adoption, and *Enforcement* in the first couple of years following policy adoption.<sup>20</sup> Third, we find greater attention to the electoral implication of adoptions in states where restrictions on smoking are more likely to be politically controversial. In particular, we would expect to find the *Electoral politics* topic to be more common in states where more people smoke, in more politically conservative states, and in states that are under Republican control. Figure B5 shows support for these expectations.

Finally, as we mention in the text, we also coded the sentiment of each topic—that is, whether the newspaper paragraph exhibited a “pro” smoking bans approach (i.e., a positive sentiment toward such bans and restrictions) or an “anti” smoking bans approach (i.e., a negative sentiment). Examining the sentiment for each topic allows us to further validate our measure. In particular, we would expect the *Health* topic to have the most positive sentiments, indicating that when this topic is discussed it is discussed in terms supportive of smoking restrictions. We also would expect that the more controversial topics such as *Bars and restaurants* and *Casinos*, which opponents of smoking bans have argued will be hurt by such bans (Warner, 2000), as well as *Enforcement*, to exhibit more negative sentiments, indicating that these are the most commonly raised arguments against smoking restrictions. And that is indeed what we find, with Figure B2 showing the *Health* topic exhibiting the most positive sentiments and *Bars and restaurants*, *Casinos*, and *Enforcement* exhibiting the most negative sentiments.<sup>21</sup>

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<sup>19</sup>Intuitively, correlations with other topics are small, with the exception of *Local legislation*, which is much less prevalent during months in which state legislation was adopted.

<sup>20</sup>We also notice a sharp drop for *Local legislation* at the time of state legislation enactment since, likely because state-wide legislation usually removes the need for legislative action at the local level. And we see an increase after adoptions for *Tobacco companies*, potentially due to lawsuits or other legal action on their part.

<sup>21</sup>It might be surprising to see *Freedom* so high on the scale, but both proponents and opponents bring up this issue, and the arguments of the former appear to dominate.

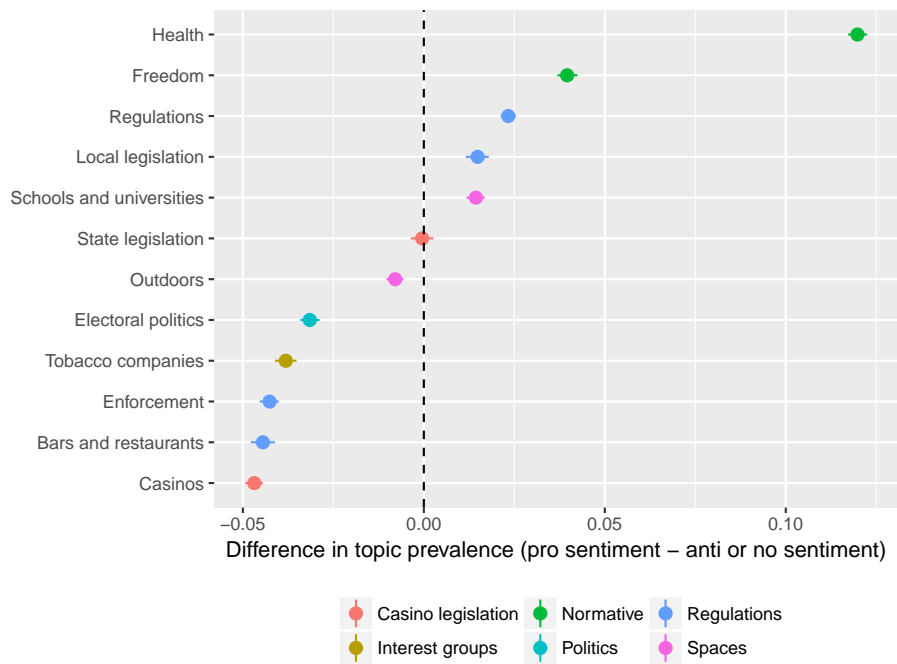


Figure B2: *Topic prevalence and sentiment.* “Pro” means that a paragraph reports facts or opinions that emphasize the success of, or need for, smoking restrictions. “Anti” denotes paragraphs conveying facts or opinions that highlight potential problems associated with smoking restrictions.

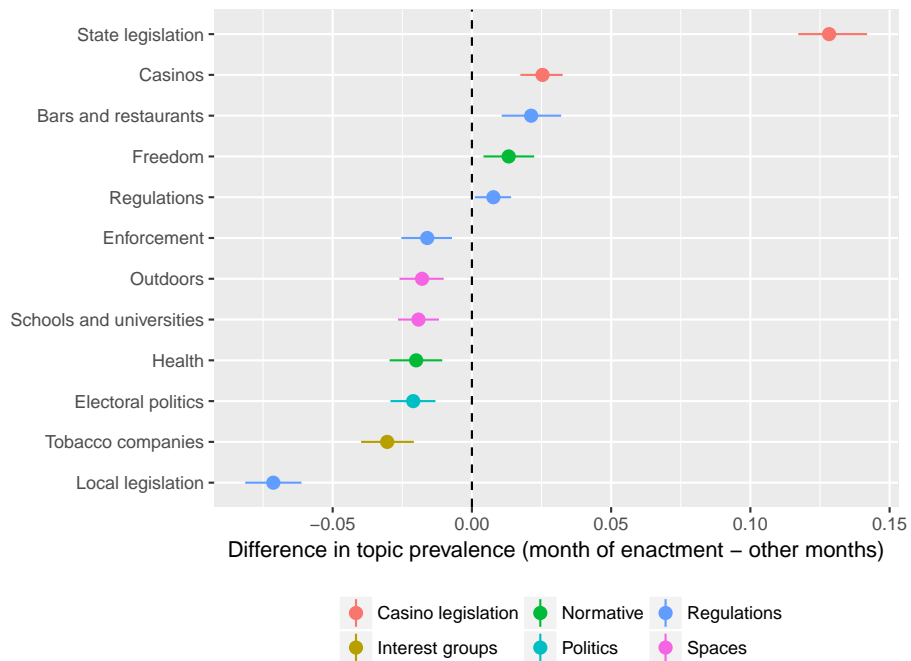


Figure B3: *Topic prevalence as a function of policy adoption at the state level in a given month.*

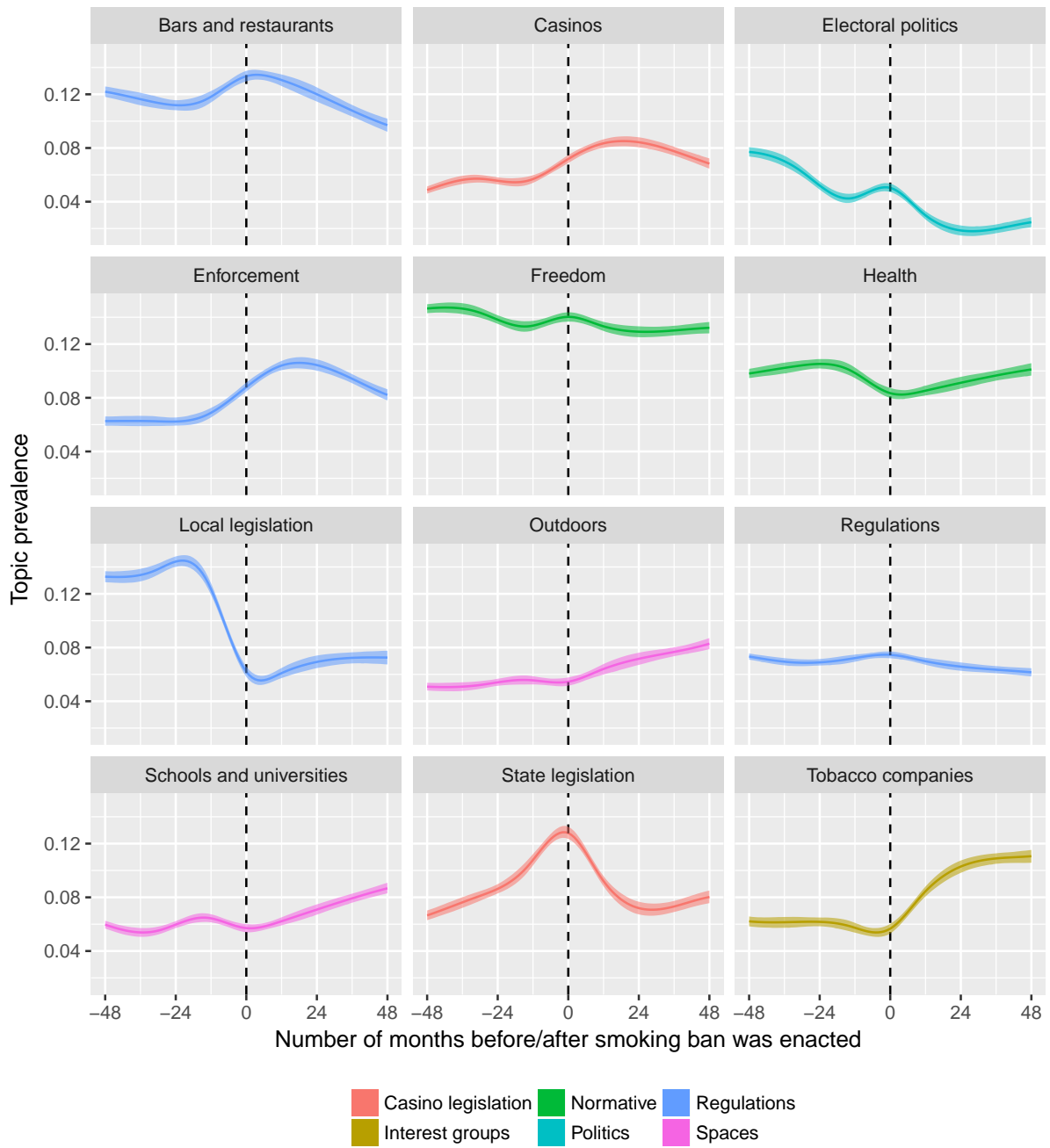


Figure B4: Topic prevalence as a function of the number of months prior to or since policy adoption at the state level.



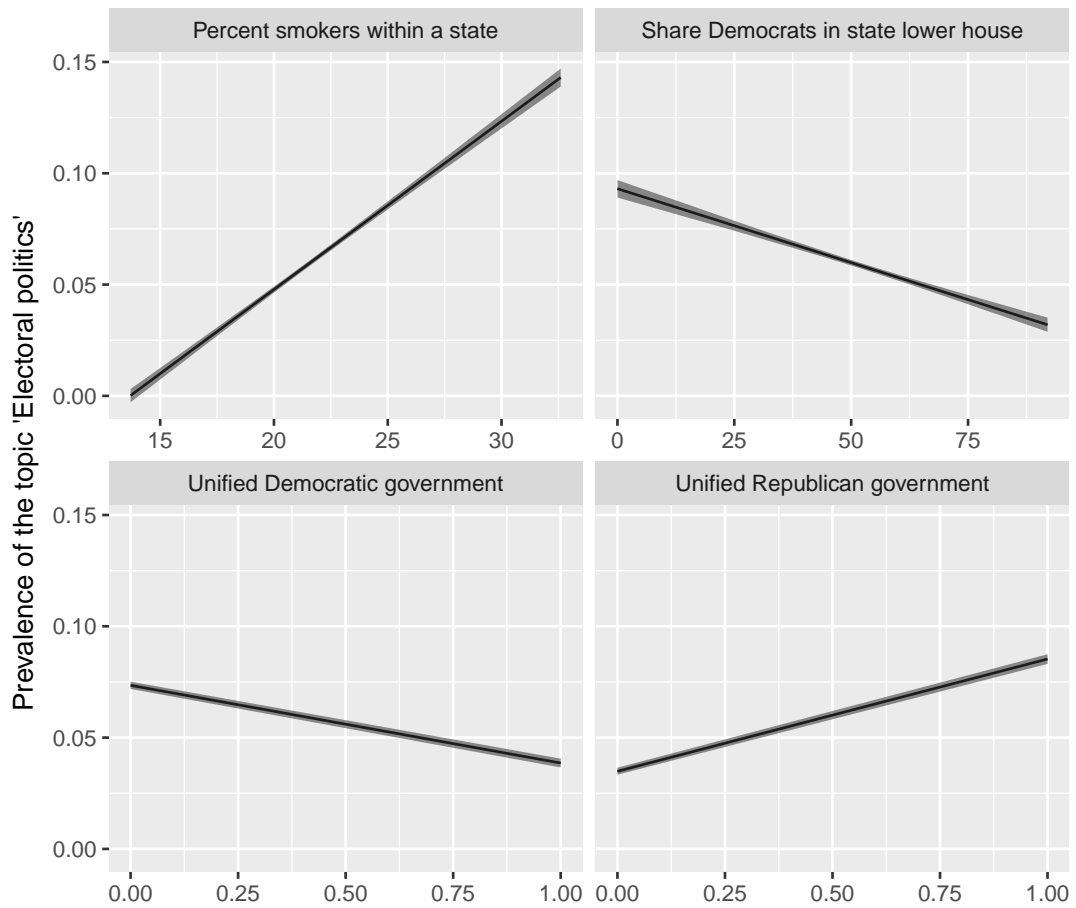


Figure B5: *Prevalence of the topic Electoral politics as a function of four variables.*

### B.3 Top-50 words for the twelve-topic model

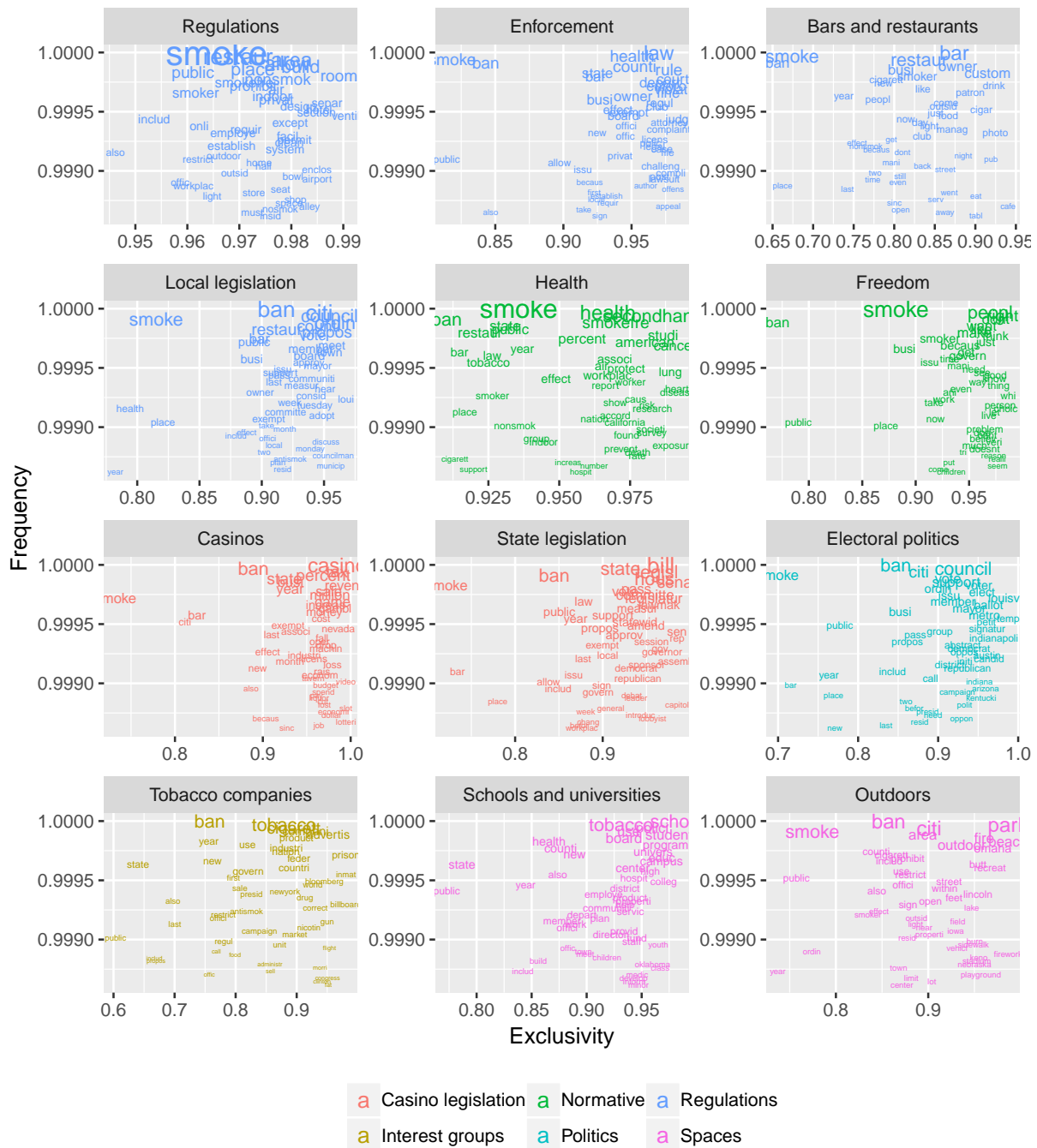


Figure B6: Top-50 words for the twelve-topic model. Exclusivity refers to the frequency with which words occur for one topic, compared to the occurrence for all other topics.

## B.4 Topic prevalence over time

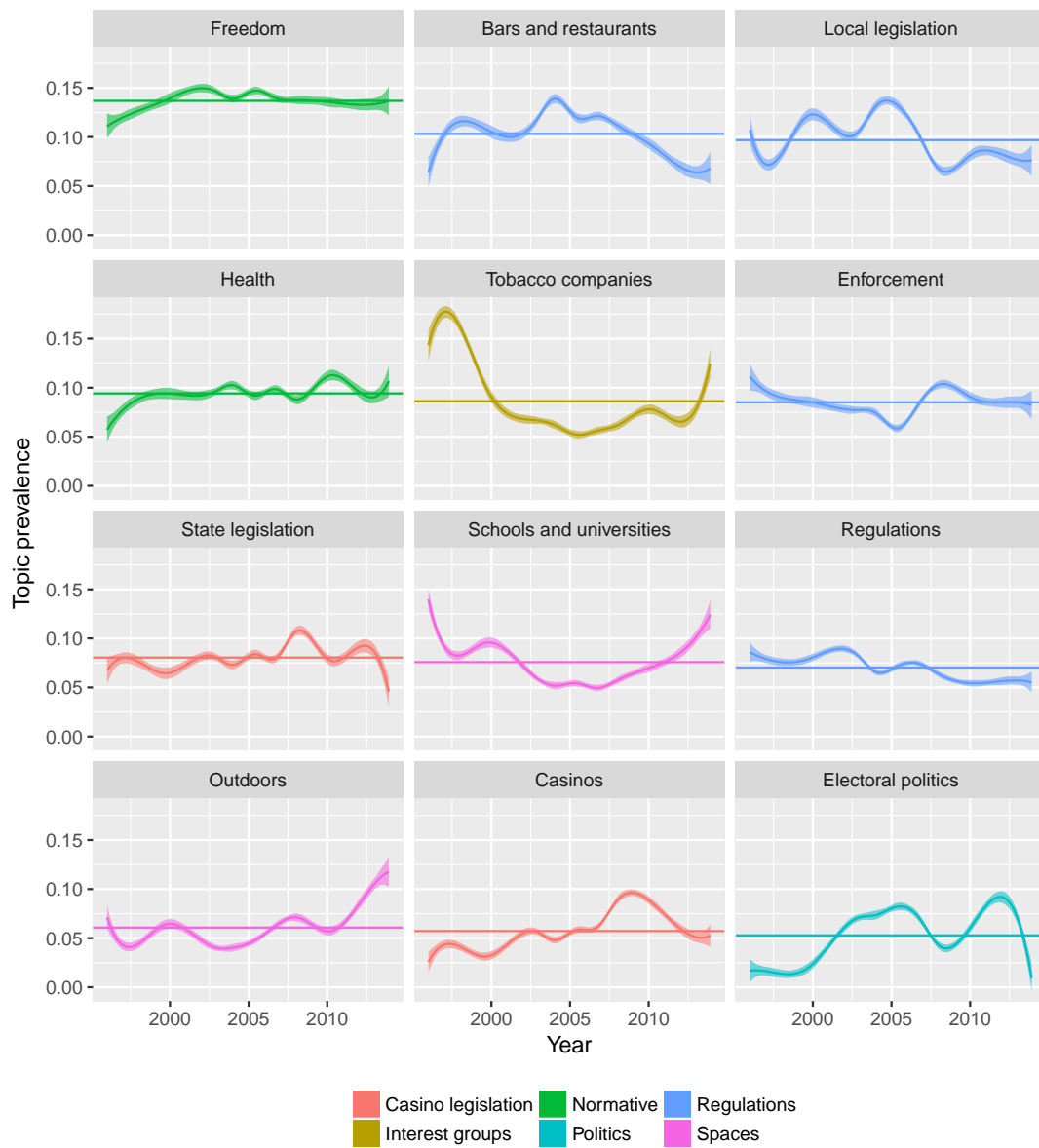


Figure B7: *Topic prevalence over time. Topics are sorted by decreasing average prevalence. Horizontal lines show average prevalence for each topic over the observation period.*

## B.5 Representative paragraphs per topic

Original text of two of the most relevant paragraphs for each topic. Relevance is based on the Maximum-a-posteriori (MAP) estimate of the modus of the proportion of words assigned to the topic.

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### *Health*

At least in a non-smoking environment smokers and non-smokers can exist. Some facts about second-hand smoke:

1. Secondhand smoke has been classified by the Environmental Protection Agency as a known cause of cancer in humans (Group A carcinogen).
2. Secondhand smoke causes approximately 3,000 lung cancer deaths and 35,000 - 62,000 heart disease deaths in adult nonsmokers in the United States each year.
3. A study found that nonsmokers exposed to environmental smoke were 25 percent more likely to have coronary heart diseases compared to nonsmokers not exposed to smoke.
4. Nonsmokers exposed to secondhand smoke at work are at increased risk for adverse health effects. Levels of ETS in restaurants and bars were found to be two to five times higher than in residences with smokers and two to six times higher than in office workplaces.

Since 1999, 70 percent of the U.S. workforce worked under a smoke-free policy, ranging from 83.9 percent in Utah to 48.7 percent in Nevada.

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#### Smoking bans help curb kids' asthma

New research shows smoking bans spare many children with asthma from being hospitalized, a finding that suggests smoke-free laws have even greater health benefits than previously believed. Other studies have charted the decline in adult heart attack rates after smoking bans were adopted.

The new study, conducted in Scotland, looked at asthma-related hospitalizations of kids, which fell 13 percent a year after smoking was barred in 2006 from workplaces and public buildings, including bars and restaurants. Before the ban, admissions had been rising 5 percent a year in Scotland, which has a notoriously poor health record among European countries. Earlier U.S. studies, in Arizona and Kentucky, reached similar conclusions. But this was the largest study of its kind – and offered the strongest case that smoking bans can bring immediate health improvements. About 40 percent of American children who go to hospitals because of asthma attacks live with smokers – a high proportion, given only about 21 percent of U.S. adults smoke, according to Atlanta's Centers for Disease Control and Prevention. The new study is published in today's New England Journal of Medicine.

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### *Regulations*

#### Rule highlights:

- Required restaurants, bars, pool halls, bingo halls and bowling alleys to be designated as entirely smoke-free or completely smoke-free, or allow smoking in designated rooms that met ventilation standards.
- Indoor workplaces, including lobbies and areas of public access, would have been required to be smoke-free or have the same ventilation standards as restaurants.

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#### No-smoking rules

- A "smoke-free" establishment prohibits smoking.
- An "effectively smoke-free" establishment limits smoking to separately ventilated areas.
- An "all smoking area" establishment permits smoking but does not have a designated nonsmoking area.
- Small restaurants, establishments that seat less than 50 people, are required to become smoke-free or effectively smoke-free.
- Larger restaurants, that seat more than 50 people, taverns and clubs can choose to become entirely smoke-free, effectively smoke-free or all-smoking.
- Indoor workplaces that employ 15 or more people are required to be entirely smoke-free or effectively smoke-free. Exceptions include private offices; indoor workplaces operated by a family with only incidental public access; and small indoor workplaces that employ less than 15 people and only incidental public access.

Source: Oklahoma Health Department

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### *Freedom*

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Letters from readers: Tyrannical smoking ban

The May 27 Star Tribune article about the smoking ban debate in St. Paul reminded me of one of my favorite quotes from C.S. Lewis: "Of all tyrannies, a tyranny exercised for the good of its victims may be the most oppressive. It may be better to live under robber barons than under omnipotent moral busybodies. The robber baron's cruelty may sometimes sleep, his cupidity at some point be satiated; but those who torment us for our own good will torment us without end, for they do so with the approval of their own conscience." Regardless of what ban supporters say, this is not about public health; it's about controlling the lives of others. These people simply cannot stand the fact that people enjoy smoking and they will use every lie in the book to try to deny people that right.

Patterson: We have, like our namesake, a libertarian streak, I guess would be a way to put it. People always want to label us, and, like everybody else, we don't like to be labeled. But we're probably somewhere between conservative and libertarian, but we definitely believe – I think it's fair to say – that government ought to respect people's freedom to live their lives as they see fit if they're not interfering with somebody else. That's sort of our outlook on a lot of the issues that come along. In fact, we believe in that so much that one of the controversies in the past that we got the most criticism on was on the smoking ban. That was the issue there to us (personal freedom). There also was a property-rights issue. Frankly, most of the things we stand for are not that unpopular with the people; they're unpopular with government. But we lost some support and some friends (over smoking), and it's not really that important of an issue. But the ability to be able to live your life as you see fit without the government telling you what to do, that is important to us.

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*Outdoors (residual)*

Rain means parks to ban fires earlier

Affected parks include Lake Pleasant, White Tank Mountain, Adobe Dam, Buckeye Hills, Estrella Mountain, San Tan Mountain, Usery Mountain, McDowell Mountain, and Cave Creek regional parks, and Spur Cross Ranch Conservation Area.

Campfires, fire pits and charcoal grills will be banned from county parks earlier than usual this year after winter rains generated extra vegetation.

Starting May 12, gas or propane grills will be the only fire allowed in county parks, and only in designated areas, the Maricopa County Parks and Recreation Department said. Violators could be subject to a fine or community service.

Parks officials are concerned that plants fed by winter rains that have since dried out could fuel brush fires.

Smoking is allowed, although people are asked to extinguish and dispose of cigarettes or other smoking materials.

Affected parks include Lake Pleasant, White Tank Mountain, Adobe Dam, Buckeye Hills, Estrella Mountain, San Tan Mountain, Usery Mountain, McDowell Mountain, and Cave Creek regional parks, and Spur Cross Ranch Conservation Area.

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In addition to the fireworks ban on the city's east side, Provo officials have also prohibited the discharge of firecrackers within 20 feet of combustible vegetation or structures.

The restricted east bench area begins east of South State Street, north to 900 East, north to Timpview Drive, north to Foothill Drive, west to Canyon Road, and north to University Avenue.

Grantsville city is restricting fireworks use until further notice to one quadrant of the city while it is banned throughout the rest of the city.

Fire restrictions are being imposed at Lake Powell and throughout the Glen Canyon National Recreation Area. The Park Service is banning all campfires, even along shoreline and beach areas as well as in developed campgrounds and picnic areas.

The use of charcoal grills also is prohibited, including those on houseboats or other vessels. Stoves fueled by propane or liquid petroleum gas are permitted. Smoking essentially is banned except inside an enclosed vehicle or at a developed recreation site.

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*Schools and universities*

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#### Tech Center to Examine I.D. Badges Carefully

New security badges that students are required to carry with them for identification at Moore Norman Technology Center will also be used to stop high school students from smoking on campus.

Last year, high school students 18 and older were allowed to smoke on campus.

Now a ban on smoking this year will keep all high school students, regardless of age, from smoking on campus.

This change was modeled after the no smoking policies of Moore Public Schools and Norman Public Schools, said Moore Norman Technology Center spokeswoman Diana Hartley.

The primary use of the badges is for identification. Employees at the technology center will wear the badges on their clothing while students will carry the badges with them, she said. Eventually, the badges will also be used to check out library books and in the grading process.

"We also plan to use it (the badge system) so that students can get a discount at restaurants and local businesses," Hartley said.

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#### Tech center adds simulated products to tobacco ban

Moore Norman Technology Center is joining a growing list of educational facilities that support and have in place a tobacco-free campus policy.

The center's board members voted recently to ban the use of all tobacco products on campus, beginning July 1. The new policy also prohibits simulated tobacco products such as electronic cigarettes or vapor inhalers.

Smoking has been banned inside the school's buildings for years, but the policy extends the prohibition to the campus grounds.

In a release about the new policy, board members said they were dedicated to providing a healthy, comfortable and productive environment for staff, students and visitors.

The center includes the Franklin Road campus at 4701 12th Ave. NW in Norman and the South Penn campus at 13301 S Pennsylvania in Oklahoma City.

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#### Local legislation

Meanwhile, Naperville officials this week delayed voting on a proposed smoking ban.

On Tuesday night after hearing speakers on both sides, the Naperville City Council delayed the vote for two weeks.

In Bartlett, efforts to pass a smoking ban also sputtered Tuesday night as officials failed to send a recommendation on a proposed smoking ban to the full Village Board for a vote.

Officials said they are trying to balance concerns about public health and the potential negative economic impact on the business community.

"That's the issue in a nutshell," said Bartlett economic development director Tony Fradin.

On March 6, the full Village Board is slated to vote on the anti-smoking measure.

Cook County's smoking ban, which county commissioners failed to delay Wednesday, goes into effect March 15.

The ban stands to affect the portions of Bartlett that lie in Cook County.

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#### County lacks votes to delay smoking ban set for March 15

Some board members sought to push back to July 2008 the smoking ban for taverns and for restaurants with bars, a date that would have coincided with Chicago's smoking ordinance.

Cook County's smoking ban will go into effect March 15 despite a last-minute attempt Wednesday by some county commissioners to delay its implementation.

Some board members sought to push back to July 2008 the smoking ban for taverns and for restaurants with bars, a date that would have coincided with Chicago's smoking ordinance.

But that proposal failed Wednesday when the County Board deadlocked 8 to 8, with Commissioner Joseph Mario Moreno (D-Chicago) absent.

The ban, approved last year, allows municipalities to opt out of the ordinance by drafting their own laws.

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#### State legislation

SB 566 by Robinson – Smoking. Would prohibit smoking in public buildings, restaurants and indoor workplaces.

Amended and passed by Senate Human Resources Committee; amended and defeated by full Senate; held on a motion to reconsider; motion to reconsider adopted; passed by full Senate; withdrawn from House Commerce, Industry and Labor Committee; passed by House Rules Committee; referred to full House. SJR 21 by Hobson – Smoking. Would prohibit smoking in restaurants and most other public places. Committee substitute passed by Senate Human Resources Committee; passed by full Senate; passed by House Rules Committee; referred to full House.

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### Senate snuffs out more restrictions on public smoking

Anti-smoking advocates suffered a major setback Tuesday when the Senate rejected a bill to place tough restrictions on smoking in public places.

After a 90 minute debate, senators voted 24-22 against Senate Bill 566, the anti-smoking bill by Sen. Ben Robinson, D-Muskogee. The measure was three votes short of the 25 needed to pass.

The rejection caused Senate leader Cal Hobson, D-Lexington, to postpone a vote later Tuesday on his anti-smoking proposal, Senate Joint Resolution 21, which has the backing of the Oklahoma Restaurant Association.

Sen. Mike Morgan, co-author with Hobson of SJR 21, conceded that Tuesday's vote on the other bill was a setback. "It's clearly a signal we're not there," said Morgan, D-Stillwater.

Robinson said he was disappointed by the vote.

His legislation would have extended a smoking ban into all indoor workplaces, public or private, with some exceptions.

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### *Electoral politics*

#### Decision on Nov. ballot inclusion due next week

Cheyenne – With 20 petition pages still to review, City Clerk Carol Intelkofer said she plans to announce early next week whether enough signatures have been collected to put Cheyenne's smoking ban on the Nov. 7 general election ballot.

The names and residency of each of the petition's signers have to be verified, Intelkofer said.

She said she has eliminated many names either because they are not city residents or because they are not registered to vote.

Both of those are key requirements for getting the measure on the ballot. In all, 2,690 signatures from qualified registered voters are required.

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#### Newcomer tests Fleming in Metro Council race

##### Democrat Blakemore stressing leadership

Louisville Metro Council incumbent Ken Fleming is facing a strong challenge from political newcomer Neville Blakemore, who is making an issue of Fleming's position on smoking curbs.

Fleming, 45, a Republican who lives in Riverwood, and Blakemore, a Democrat who lives in Druid Hills, are vying in the Nov. 7 election to represent District 7, which also includes parts of St. Matthews, Indian Hills and other small cities in eastern Jefferson County.

Ken Fleming 45, incumbent, Republican, vice president of LandAir Mapping Inc.: "I supported the most recent comprehensive smoking ban.

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### *Enforcement*

#### Smoking ban filed properly, agency says; Nitro Moose petition alleges new rule wasn't

A Kanawha-Charleston Health Department administrator says the agency properly filed its expanded smoking ban regulations with the Kanawha County clerk's office, and she's got the documents to prove it. The Health Department filed the regulations on Dec. 11, 2007, five days after the agency recorded the same rules at the Charleston city clerk's office, said Administrative Services Director Lolita Kirk. The Nitro Moose Lodge filed a petition in Kanawha County Circuit Court last week, alleging that the smoking ban doesn't apply to bars outside Charleston's city limits because the Health Department failed to file the regulations with the county clerk's office.

The expanded smoking ban took effect July 1, and the Moose is one of six Kanawha County businesses that face misdemeanor charges for allegedly violating the smoking regulations.

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#### Bar owner's smoking ban suit dismissed

Abstract: In a three-paragraph memorandum issued Thursday, the appellate court said the lawsuit was moot because the bar, Sporty O'Toole's, had since gone out of business and owner Boyd Cottrell told the court he doesn't plan to open another. Because the bar is closed, it's no longer affected by the ban, therefore there's no reason to continue the lawsuit, the court said.

Free Press Staff Writer

A Warren bar owner's lawsuit challenging the state's smoking ban was dismissed by the state Court of Appeals without the court addressing the issue of the law's constitutionality.

In a three-paragraph memorandum issued Thursday, the appellate court said the lawsuit was moot because the bar, Sporty O'Toole's, had since gone out of business and owner Boyd Cottrell told the court he doesn't plan to open another.

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### *Tobacco companies*

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The company has made that point in broadcast advertisements, in fliers it has inserted in cigarette packs from 2002 to 2009, on its website and on tear-tape on cigarette packages, he said. "We will continue to communicate that there is no safe cigarette," Phelps said.

In addition to the ban on the terms "light," "ultra-lights," "mild," "smooth" and "low-tar" in describing cigarettes, the key new FDA regulations:

- require larger and more strongly worded warnings on smokeless tobacco packaging and in advertising;
- make it a federal violation to sell cigarettes or smokeless tobacco to minors;
- ban selling packs of fewer than 20 cigarettes (to keep the cost out of reach of minors); and
- ban tobacco brand-name-labeled giveaways, such as T-shirts or hats, with purchases of cigarettes or smokeless tobacco.

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Europe Trade Bloc OKs a Phased-In Ban of Tobacco Ads; Regulation: Move by health ministers of 15-nation EU also targets sponsorship of cultural, sports events. Cigarette firms vow fight to 'communicate with consumers.'

Health ministers from Western Europe, where smoking is blamed for more than half a million deaths each year, overcame eight years of deadlock Thursday, agreeing to phase in a ban on tobacco advertising and sponsorship of sports and cultural events by tobacco companies.

Under the European ban, which goes much further than the U.S. ban on tobacco ads on television and radio in effect since the 1970s, most advertising, including on billboards, must cease within three years. Ads in media printed in Europe, including newspapers and magazines, must end within four years. Indirect advertising, such as apparel bearing the name of cigarette brands, would have to end within six years. Although more sweeping, the European ban is not nearly as immediate as the advertising restrictions contained in the proposed U.S. tobacco deal announced June 20. Under the sweeping American agreement, negotiated among cigarette makers, state attorneys general and private anti-tobacco lawyers, tobacco billboards and sponsorship of sporting and cultural events would be banned almost right away, as would caps, shirts and other items carrying tobacco logos.

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#### *Bars and restaurants*

Galen Sprague and Marchello Marchese, who say they don't mind stepping outside to take a cigarette break, join other smokers outside the Lansdowne Street clubs during the wee hours of May 10, on the first weekend since Boston's smoking ban went into effect.

Caption: Globe Staff Photos / David Kamerman

Ban on smoking begins to open doors for diners

Jean Reagan, 77, a smoker for 60 years, sits Monday in the smoking section of the Four Coins Restaurant in St. Petersburg.

Photo: James Borchuck

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#### *Casinos*

Colo. casino revenue declined 12% in 2008

Colorado's mountain-casino revenue dropped nearly 17 percent in December, wrapping up a year in which the industry suffered declines every month.

For 2008, casinos statewide reported adjusted gross proceeds, or total bets minus payouts, of \$715.8 million, down 12 percent from \$816.1 million in 2007, according to data released Wednesday by the Division of Gaming. It was the worst annual drop for the industry since casino gambling launched in the state in October 1991.

The industry has attributed the struggles largely to the sluggish economy and a smoking ban that went into effect in January 2008. Some officials have also pointed to high gas prices during the first half of last year.

Black Hawk's 20 casinos generated \$508.6 million in adjusted gross proceeds in 2008, down 12.5 percent from \$581.3 million in 2007. Cripple Creek's 16 casinos produced \$140 million, down 9.6 percent, and Central City's six casinos totaled \$67.1 million, down 15.9 percent.

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#### *Herbst Gaming seeks debt fix*

Herbst Gaming, which has taken a financial hit in the past year after a statewide smoking ban cost the company customers in its slot machine route operation, has asked Goldman Sachs to assist in evaluating financial and strategic alternatives, including the sale of the business.

In a statement released Wednesday, Las Vegas-based Herbst Gaming, which significantly grew its statewide casino business through two high-profile acquisitions in 2007, said the alternatives could include a recapitalization, refinancing, restructuring or reorganization of the company's debt, or a sale of some or all of its businesses.

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## C Extrapolation of diffusion networks

The binary diffusion ties in the policy diffusion networks in [Desmarais et al. \(2015\)](#) are inferred from diffusion cascades of 160 policies and cover the years from 1960 to 2009. The paragraphs in our corpus were published in the time period from 1996 to 2013, which is why we need to extrapolate the existing diffusion network data for the four years from 2010 to 2013. In order to achieve this, we fit four separate temporal exponential random graph models (tergm) as follows. For each extrapolation, a series of networks is created that corresponds to the time interval which is extrapolated (1 year for 2010, 2 years for 2011, etc.). For example, to extrapolate to 2010 (1 year time interval), we fit a tergm model to 2006, 2007, 2008 and simulate for 2009. This simulation is evaluated against the existing network data for 2009. For each of the models the optimal combination of the following network statistics is then used to predict the missing year: the baseline probability of establishing edges in the network, the square roots of the indegree and outdegree centralities of each node, the edge innovation and edge loss statistics, and a temporal lag in form of a reciprocity term delayed by a single time period. The following table reports the out-of-sample evaluation for the four extrapolated years:

Year	Precision	Recall	F1 score
2010	0.77	0.87	0.82
2011	0.90	0.78	0.83
2012	0.91	0.77	0.83
2013	0.89	0.78	0.83

## References (Appendix)

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