Policy Diffusion: The Issue-Definition Stage*

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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 structural topic models to estimate how policies are framed and how these frames vary as a function of prior policy adoptions. Focusing on restrictions on smoking in U.S. states, our analysis draws upon an original dataset of more than 3.1 million paragraphs from newspapers covering 49 states between 1996 and 2013. We find that frames are related to prior adoptions within a state's diffusion network, but this holds true only for frames regarding the policy's concrete implications and not those considering normative justifications. These findings open the way for a new perspective to studying policy diffusion in many different areas.

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1 Introduction

Policy diffusion is the process by which policymaking activity in one government affects policymaking activity in other governments. This process can take many forms. For example, diffusion can be horizontal, with policy actions diffusing from city to city, state to state, or country to country. Or it can be vertical, with the actions of national governments affecting those of subnational governments, with supranational governments affecting the actions of national governments, or with the actions of cities affecting those of states. Regardless of the specific form, the central idea behind the concept of diffusion is that policymaking is a process marked by interdependency among political units.

This process of diffusion has been the focus of a large and rapidly growing number of studies (see recent reviews by Graham, Shipan and Volden, 2013; Maggetti and Gilardi, 2016; Boehmke and Pacheco, 2016). Most generally, these studies have convincingly established, across a wide range of policy areas and governments, that policies do indeed diffuse. More specifically, there is now a vast amount of accumulated evidence showing that policy *adoptions* diffuse, with adoptions in one unit influenced by prior adoptions in other units.

That scholars have concentrated mainly on adoptions is understandable. Adoptions can be observed and measured with relative ease. They obviously constitute an important political activity. And the study of adoptions has built directly on the initial and pioneering studies of policy diffusion (e.g., Walker, 1969) to produce numerous insights. At the same time, this nearly singular attention to adoptions means that most studies of diffusion have neglected what policy scholars long have recognized: that the life cycle of policymaking has multiple distinct stages. Before policies can be adopted, they must be formulated; and before they can be formulated, they must be defined and placed on the agenda. In other words, a starting point for the policymaking process is *issue definition*, which captures how potential policies are perceived, or framed.[1]

This recognition that policymaking goes through several stages has a significant, if heretofore overlooked, implication for the study of diffusion. For policy adoptions in earlier states to influence the eventual adoption decisions of other states, these previous adoptions first must affect the ways in which these other states (i.e., those that have not yet adopted the policy) think about and define the policy in question. Put more succinctly: in order to have a better understanding of the diffusion process, we must examine whether and how prior adoptions influence the way in which an issue is later defined

[1]Unless otherwise noted, we use the terms *issue definition* and *policy framing* interchangeably throughout the paper.

in these other states. Concretely, in our analysis we treat issue definition as an outcome and examine whether and how previous policy adoptions are associated with changes in how an issue is defined or framed. We enter uncharted territory in doing so: there is no conventional wisdom on this question.

To examine whether and how prior adoptions are related to issue definition, our empirical analysis focuses on anti-smoking laws—that is, policies restricting or banning smoking in public places—in the U.S. states. We compiled an original dataset of more than three million paragraphs from articles published in 49 American newspapers covering 49 states between 1996 and 2013. With this dataset in hand, we use structural topic models (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016) to estimate how this policy has been framed in the states and to show how these frames vary as a function of prior policy adoptions by other states.

This approach allows us to make several notable contributions. Our main contribution is both theoretical and empirical: we demonstrate why and how studies of policy diffusion should take the issue-definition stage, and the framing that occurs at this stage, into account. In particular, our approach allows us to assess whether and how prior adoptions are related to a frame's prominence and how those frames change over time. We do this, first, by identifying frames, and second, by examining whether prior policy adoptions in other states are linked to the ways in which anti-smoking policies end up being defined and discussed. When more states adopt anti-smoking policies, for example, do some frames become more prominent? Do previously prominent frames lose salience when policies become widespread?

We find that, controlling for many relevant factors, the frames used to describe smoking restrictions and bans in a given state are related to the prevalence of the policy within that state's diffusion network (which we define in more detail later, based on Desmarais, Harden and Boehmke 2015). More specifically, our analysis shows that the diffusion of smoking bans shifts attention from tobacco companies to voters, from the technical details of the restrictions to their enforcement, and from potential costs for bars and restaurants to potential problems for casinos. However, two important frames—individual rights and public health, which are two of the main rationales raised in debates over smoking restrictions—are unrelated to prior adoptions. Thus, our analysis shows that diffusion is strongly related to the way smoking bans are framed in areas in which information on the policy's concrete implications emerges from other states. By contrast, normative justifications such as individual rights and improved health are less susceptible to change following policy diffusion.

Our contributions are also methodological. At a general level, we demonstrate that using modern text analysis methods, and structural topic models in particular, allows us to develop measures of issue definition based on a large number of articles across dozens of newspapers and across time.[2] At a more specific level, we show how structural topic models can be used to provide new insights into diffusion. In part, using these models allows us to pursue theoretical and substantive questions related to policy diffusion, where we recognize that policy does not proceed directly from adoption in one place to adoption in another, but rather from adoption in one place to the start of the policymaking process (i.e., issue definition) in another state. But it also broadens the ability to study diffusion in that adoptions are relatively infrequent events, with not all policymaking efforts resulting in new policies, or even in concrete policy proposals. Adoptions either happen or do not happen, and can be rare. Consideration of new policies, on the other hand, occurs frequently; and issue definition can take on a wide variety of forms. 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 Our Approach and Expectations

Studies from several different strands of research inform our investigation into whether prior policy adoptions in other states influence issue definition in future states. Since our primary goal is to deepen our understanding of policy diffusion, we situate our study directly within the literature on this topic. As noted above, 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 analyzed the relationship between prior adoptions and these earlier stages.

One study that does consider earlier stages is Pacheco (2012), which finds that earlier adoptions can affect public attitudes toward policy in other states that have not yet adopted the policies in question. Another important exception is Pacheco and Boushey's (2014) investigation of whether prior policy adoptions increase the amount of attention that states pay to a policy area, with attention measured by the number of bills introduced in states that have not yet adopted the policy. And Karch (2007) pays

[2]For recent and similar effort to use machine learning approaches to determine how issues have been defined in the U.S. states, see the Policy Frames Codebook project (Boydstun et al., 2014), the Media Frames Corpus project (Card et al., 2015), and Baum, Cohen and Zhukov's (2017) analysis of newspapers' coverage of rape culture.

careful attention to the agenda-setting stage within a diffusion framework, using newspaper coverage as an indicator of an issue's visibility.

By and large, however, studies in the diffusion tradition have centered their attention on the adoption of policy in later states. To be clear, not all studies have looked only at whether later adoptions are a function of earlier adoptions. Scholars have, for example, examined how features of policies (e.g., cost, complexity, etc.) affect policy adoptions and the rate of diffusion (Makse and Volden, 2011; Boushey, 2010). Our point is that studies of diffusion, by generally treating later policy adoptions as the feature to be explained, have neglected earlier stages in the policymaking process.

If we want to understand the relationship between prior adoptions and the overall policymaking process in later states, the literature on the life cycle of public policies—which emphasizes the importance of the issue definition stage—strongly suggests that we should examine the influence of prior adoptions on the ways in which future states define issues.[3] As we have already discussed, policies advance through a series of stages, including several stages that necessarily occur prior to adoption (e.g., Anderson, 2014; Patton, Sawicki and Clark, 2015). At the start of the policymaking process—before policy alternatives are placed on the agenda, before policy alternatives are formulated, before adoption can take place—issues need to be identified and defined.[4] Hence, issue definition is a logical starting point for the policymaking process, with changes in issue definition producing shifts in the agenda (Kingdon, 1984; Baumgartner and Jones, 1993; Wolfe, Jones and Baumgartner, 2013), as well as other downstream effects.[5]

Although there are countless studies of issue definition, from the viewpoint of our analysis Boushey's (2016) innovative investigation of the adoption of criminal justice policies stands out. His study 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. Boushey looks at how the definition (or more specifically the social construction) of an issue affects its diffusion, whereas we

[3]Although throughout this paper we generally combine the concepts of issue definition and policy framing, here we separate them in order to highlight distinct (although related) aspects of each: that studies of issue definition (and the policy lifecycle) have emphasized the ways that decisions at this stage affect later stages; and that studies of framing have shown that because policies are multidimensional, they can be framed in multiple ways.

[4]Indeed, as Elder and Cobb cogently observed, "policy problems are not a priori givens but rather are matters of definition," and therefore "what is at issue in the agenda-building process is not just which problems will be considered but how those problems will be defined" (Elder and Cobb, 1984, 115).

[5]For example, issue definition can influence the ways in which policy alternatives are designed—in other words, it can affect the policy formulation stage of the 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. More generally, Boushey (2016) observes that the influence of issue definition on later stages in the policymaking process, including adoption, is "nearly axiomatic" within the policymaking literature, noting the myriad of classic studies (e.g., Kingdon, 1984; Elder and Cobb, 1983) that have established such links.

focus on how diffusion can produce different issue definitions over time and across governments. Thus, our study and his are complementary, with his examining how frames can lead to adoptions, while ours looks at how adoptions can influence frames.

Studies of how policies are framed—and in particular the existence of multiple competing frames—provide another marker for our study. Several recent analyses have demonstrated that public policies can be framed in different (and competing) ways, and that the choice of frames—or what Baumgartner and Jones (1993) call "policy images"—can influence subsequent stages of the policy process. One of the best-known studies of policy framing is Baumgartner, De Boef and Boydstun's (2008) investigation of the death penalty. Drawing on hand-coded abstracts of articles about the death penalty in the *New York Times*, these authors establish that the dominant frame of this issue changed dramatically over time, with frames relating to the constitutionality and morality of the death penalty giving way to an emphasis on the potential innocence of convicts who were sentenced to death.[6] Similarly, Haynes, Merolla and Ramakrishnan (2016) code stories about immigration in four newspapers and three cable networks to examine how immigration policies (and immigrants themselves) are framed in the media. Their analysis shows that the way in which a policy is framed significantly affects public attitudes toward that policy.[7]

We build on the studies of these issues—policy diffusion, issue definition, and framing—in order to determine whether and how prior adoptions influence the way issues are then defined and discussed in future states. Our most general goal is to examine whether such a link exists and what it looks like, where the ways in which an issue is defined and framed is a function of these earlier adoptions—a question for which no conventional wisdom exists. Within this general framework we have two more specific expectations.

First, our primary expectation is that *issue definition within a state should be linked to prior adoptions by other states within that state's diffusion network*. At the heart of diffusion is the idea that policymaking processes are interdependent. To capture this interdependence, most scholars have relied on measures such as geography (e.g., looking to see whether states are influenced by adoptions in geographically

[6]They also show that this shift produced changes in public opinion and in policy outcomes, as measured by the number of death sentences.

[7]See also Bosso's (2017) investigation into the framing of the 2014 farm bill and VanSickle-Ward and Wallsten's (2017) study of how birth control policies are framed. Closer to the empirical focus of our paper, several studies have shown that the success of tobacco policies is closely linked to their framing. Jacobson, Wasserman and Raube (1993) document how early setbacks in anti-tobacco legislation were due to "the manner in which the legislative debate is framed by antismoking advocates and the tobacco industry" (Jacobson, Wasserman and Raube, 1993, 789). Menashe and Siegel (1998) similarly observe that "the tobacco industry has created a central message and theme which has been used constructively and consistently over time" (Menashe and Siegel, 1998, 307). See also Harris et al. (2010).

contiguous states) or other similarities (e.g., whether states are influenced by adoptions in states that share similarities other than geography, such as ideology or partisanship). Recently, however, Desmarais, Harden and Boehmke (2015) developed and applied an algorithm that allows scholars to determine the underlying network of states within which policies will diffuse. We draw upon their approach, which we discuss in detail in Section 3.4, in order to study the link between prior adoptions and issue definition.

Second, we expect our method to capture the frames that public health scholars have identified: health effects, economic consequences, freedom and rights, and practical considerations about implementation (Jacobson, Wasserman and Raube, 1993; Menashe and Siegel, 1998; Magzamen, Charlesworth and Glantz, 2001; Champion and Chapman, 2005). These frames provide a baseline for what we should expect to find, and thus act as a basic check on whether our approach—which, unlike these previous studies, relies on a computer-based analysis and a large volume of text—is on the right track. But we also expect our analysis to go beyond these earlier studies—either because they were limited to a single type of policy, such as restricting smoking in bars (e.g., Champion and Chapman, 2005; Magzamen, Charlesworth and Glantz, 2001), or a limited set of states (Jacobson, Wasserman and Anderson, 1997), or a small number of newspaper articles (Menashe and Siegel, 1998)—and to find additional frames. In particular, we expect to find that debates focus not only on bars, but also on smoking restrictions in other highly prominent (and potentially controversial) locations. In addition, we expect to find frames that underscore the inherently political nature of the debate over smoking, including specific references to the role of legislative and electoral politics.

Overall, then, our main expectations as we conduct our empirical analysis are that we should find frames that earlier, more labor-intensive, and smaller-scale studies of framing also uncovered; that we should find additional frames that were not identified by these earlier studies, due to their limitations; and, most importantly, that issue definition should be a function of earlier adoptions by other states that fall within a state's diffusion network.

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 frames. Here, we follow DiMaggio, Nag and Blei (2013) and Nowlin (2016), who argue that topic models are an ideal tool to identify frames in texts. Specifically, DiMaggio, Nag and Blei (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 constitute "the smallest units of framing" (Baumgartner, De Boef and Boydstun, 2008, 107). Individual topics might be "used in conjunction with one another to form a larger cohesive frame" (Baumgartner, De Boef and Boydstun, 2008, 136), but our approach focuses on the building blocks with which more complex frames might be constructed.

3 Methodology

3.1 Case selection

Our analysis of policy frames as a part of the diffusion process concentrates, as noted earlier, on the adoption of antismoking policies in US states. US states historically have had considerable autonomy in public health areas, and smoking restrictions are no exception. Although smoking-related issues are often discussed by politicians at the national level (McCann, Shipan and Volden, 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, 2014; Rogers and Peterson, 2008; Pacheco, 2012), as well as abundant anecdotal evidence, indicate that smoking bans have exhibited a diffusion process. This allows us to concentrate on the nature of the process—in particular, the ways in which this issue is defined—rather than the mere existence of diffusion. Second, smoking bans have been adopted in a convenient time frame—roughly a fifteen-year period—that is long enough to detect variations and to supply sufficient information, but short enough to be practically manageable. Third, the policy has well-defined characteristics and is comparable across units. Fourth, 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 (e.g., Studlar, 1999; Jacobson, Wasserman and Anderson, 1997). And finally, this uncertainty over consequences means that the debate over adoption can be framed in multiple ways.

3.2 Corpus

The time period we examine begins in 1996, which is two years before the first statewide smoking ban was adopted in California.[8] 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 Appendix A). 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 time period for most newspapers. We use print media rather than television or radio programs partly for technical reasons but especially because they generally 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 can expect that newspapers 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 the nature of public discussion" (Baumgartner, De Boef and Boydstun, 2008, 20).

We retrieved newspaper texts using a simple, broad keyword search from different database providers. Then we split the texts into paragraphs of a similar length and removed duplicate paragraphs, which produced a corpus containing 3,159,350 paragraphs. We provide more details on these procedures in Appendix B. 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 Crowdflower to annotate a sample of about 10,000 paragraphs as relevant or irrelevant. We followed the procedures explained in Benoit et al. (2016) and found that the crowd annotation produced results comparable with three expert codings. Appendix C discusses 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

[8] 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.

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.[9] Next we evaluated seven algorithms[10] 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 Appendix D, support vector classifier worked well, producing a final corpus of 52,675 paragraphs.

3.3 Structural Topic Model

We identify policy frames inductively with a structural topic model (STM) (Roberts et al., 2014; Roberts, Stewart and Airoldi, 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 (LDA) model (Blei, Ng and Jordan, 2003). These models are mixed-membership, that is, they assume that each unit of text (i.e., in our case, each paragraph) consists of a mixture of topics (Grimmer and Stewart, 2013, 283–285). As a consequence of the logistic-normal distribution underlying these models, topic prevalences always add up to 1 for each document. Therefore, if a topic has a higher-than-average prevalence in a document, it lowers the prevalence of the other topics. This assumption is very realistic: if a given topic takes up more space in a text, it necessarily reduces the attention given to other topics. Moreover, the assumption is consistent with the strategy used by Baumgartner, De Boef and Boydstun (2008) to manually code all existing component parts of frames for every document.

The STM's major innovation is that the prior distribution of topics can vary as a function of covariates (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016). The inclusion of covariates in the topic model makes it possible to test hypotheses 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 examine directly our main expectation, namely, that topic prevalence within a state—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

[9] 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.

[10] Ada boost, Bernoulli naïve Bayes, Gaussian naïve Bayes, K-nearest neighbors vote, random forest, support vector machines, and logistic regression.

factors that may be related with topic prevalence. We discuss the covariates that we include in our analysis in Section 3.4.

We estimate our topic models using the `stm` package in R (Roberts, Stewart and Tingley, 2014). We initialize the models with the spectral algorithm, which is robust to changes in several CTM parameters and starting values (Roberts, Stewart and Airoldi, 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. We describe this step of the analysis in more detail in Appendix E. After a qualitative evaluation of the most-probable words[11] and documents of the models' topics in this range, we selected the 12-topic model as the most useful for our analysis. However, we report the results of models assuming 3 to 13 topics in Appendix F, which shows that the models identify the same underlying topics, although obviously with different degrees of granularity.

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 simply 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 a 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 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 the policies of which other states. Traditionally, the literature has simply relied on geographic proximity, a catch-all indicator that is theoretically blunt (Maggetti and Gilardi, 2016). Instead, we use the dataset constructed by Desmarais, Harden and Boehmke (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

[11] The probability of observing each word in the vocabulary under a given topic, or β, is one of the main outputs of the STM (Roberts, Stewart and Airoldi, 2016). For the most probable word lists per topic, words are simply ranked according to their topic-specific probability.

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, Harden and Boehmke, 2015, 395). That is, they estimate, for each year, which pairs of states are connected by "diffusion ties"—that is, for each pair of states, whether policies diffuse from one to the other, and in which direction. The result is a directed dyadic dataset that can be easily 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.[12] As Desmarais, Harden and Boehmke (2015, 397) note, "the overwhelming majority of policy diffusion relations exist between states that are *not* geographically contiguous" (original emphasis).

Another important covariate is the sentiment of a given paragraph. To measure sentiment, we relied on the same approach we used for the identification of relevant paragraphs, which we explained in detail in Section 3.2. First, we crowd-coded the sentiment of a sample of 10,000 relevant paragraphs based on a custom definition of sentiment. 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.[13] Prior to the classification, the paragraphs were pre-processed in the same way as for the relevance filter.[14] We include the measure of sentiment obtained by this procedure as a covariate in the analysis.

In addition to sentiment and the share of prior policy adoptions within a state's diffusion network, the analysis includes several other covariates, which we use to control for important 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 the ideological leaning of a newspaper might affect its coverage of smoking bans; (4) the percentage

[12]Since the policy 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, Harden and Boehmke (2015). We discuss this procedure in Appendix G. The forecast was designed and implemented by Fridolin Linder.

[13]There were also paragraphs in which there is no sentiment or in which both pro and anti sentiments were equally present. We asked crowd-workers to code these paragraphs into a separate category. However, since there are few paragraphs in this category, we combined it with the "anti" category for the machine-learning classification.

[14]In the evaluation of the machine learning, an ensemble of ada boost, Bernoulli naïve Bayes, K-nearest neighbors vote, random forest, and logistic regression models provided the best solution for retrieving pro sentiments (recall of 0.82 and precision of 0.69).

of smokers in the state where the newspaper is based; (5) whether a newspaper is based in a tobacco-producing state, since these two variables might be related to the popularity of smoking bans; (6) whether Democrats or Republicans form a unified government in a state, because Democrats and Republicans tend to have different views on smoking restrictions; (7) the presence of smoking bans in a state; and (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.

4 Results

The discussion of our results proceeds in three steps. First, in Section 4.1 we present the topics identified by our STM (Figure 1) and their distribution over time (Figure 2). Second, in Section 4.2 we validate the topics, including a discussion of their correlation with sentiment (Figure 3). Third, and most importantly, in Section 4.3 we show how policy frames are related to policy diffusion—that is, how topic prevalence is linked to prior policy adoptions within a state's diffusion network (Figure 4).

4.1 Topics

For the reasons explained in Section 3.3, we present here the results of a model assuming 12 topics. Figure 1 shows the top-50 words associated with each topic, along with labels that we assigned to each topic based on both the top-50 words themselves and also a reading of the most relevant paragraphs for each topic, which are shown in Appendix H. The interpretation of the topics is quite straightforward and their connection with smoking bans clear—indeed, the frames that public health experts had previously identified all emerge from the data, lending strong support to the validity and value of our approach. Overall, our model identifies relevant and meaningful topics, and does so to a surprising extent, given that they were produced purely inductively, without human input apart from the selection of the number of topics.

The twelve topics can be grouped into four categories. First, we have topics referring to _Locations_—particular types of establishments, buildings, or areas affected by smoking bans, such as *Bars and restaurants*, *Casinos*, and *Schools and universities*.[15] A second set of topics focuses on _Politics_. This category includes *Local legislation* and *State legislation*, which identify decision-making and legislative

[15] *Outdoors* might also belong to this category, but an examination of both the top words and the paragraphs shown in Appendix H indicates that this topic is about activities susceptible to causing outdoor fires, such as fireworks. Accordingly, we will not interpret this topic further.

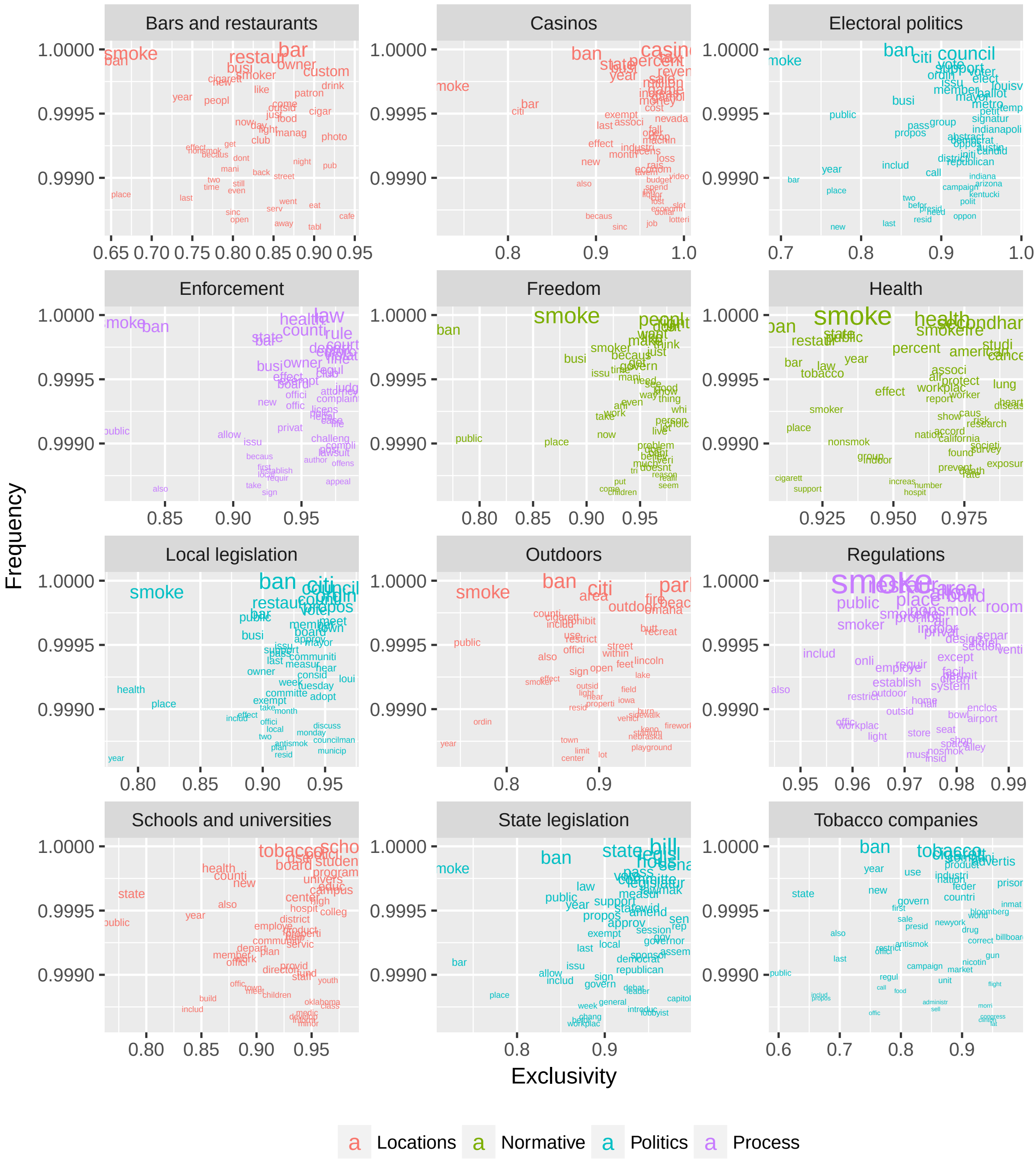

Figure 1: *Top-50 words for the twelve-topic model. Exclusivity refers to the frequency with which words occur for one topic, compared to the occurrence for all other topics, estimated following Bischof and Airoldi (2012).*

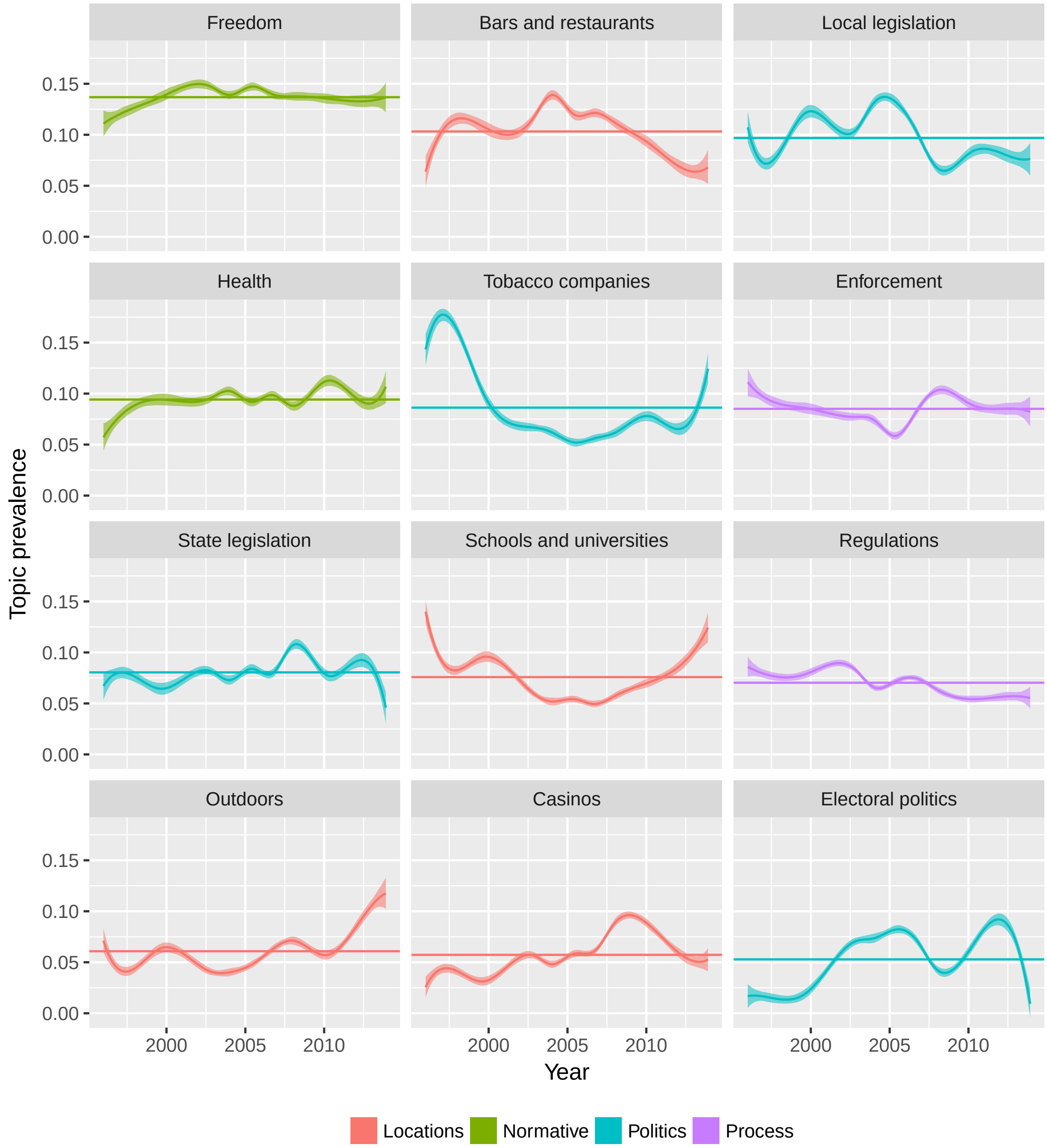

Figure 2: *Topic prevalence over time. Topics are sorted by decreasing average prevalence. Horizontal lines show average prevalence for each topic over the observation period.*

action at the local and state levels; *Electoral politics*, which emphasizes the involvement of voters in policymaking, such as the role smoking bans play in elections or direct-democratic initiatives such as petitions; and *Tobacco companies*, which identifies the most powerful interest group in this area. Third, there are topics that we label <u>*Process*</u>. In this category, *Regulations* and *Enforcement* identify concrete aspects of smoking bans, namely the specific rules devised for prohibiting smoking and their implementation. Fourth, *Freedom* and *Health* refer to two of the main <u>*Normative*</u> arguments in favor of or against smoking bans, where the former refers to debates on the compatibility of such bans with individual freedom and choice and the latter to the idea that the policy improves health outcomes.

Figure 2 shows the distribution of the prevalence of these topics over time, as well as each topic's average prevalence over the observation period. A few findings stand out. The most prevalent topic, on average, is *Freedom*—which comes as little surprise, given the intense debate over the compatibility of smoking bans with individual rights, and given that prior public health analyses highlighted the importance and prevalence of this frame. Notably, this topic's prevalence is relatively constant over time, indicating the persisting nature of this controversy. The second-most frequent topic is *Bars and restaurants*, whose relevance in smoking bans debates has been clear both to casual observers and advocates of restrictions (Champion and Chapman, 2005). Contrary to *Freedom*, the topic *Bars and restaurants* shows significant variation over time, especially a decrease in prevalence after 2005. *Local legislation* is the third-most-frequent topic. Many smoking bans have been enacted at the local level. *Health* is among the most frequent topics, but is not *the* most frequent, as some might expect. Its prevalence is relatively stable over time. *Tobacco companies* have been one of the main actors in this area, and the topic is the fifth-most-frequent one in our corpus. Its prevalence was extremely high in the 1990s but decreased afterwards. The other topics follow. Noteworthy is that *Electoral politics* is, on average, the least frequent topic. The connection between smoking bans and voters is clearly not one of the main themes in our corpus, although there is significant variation over time.

We conclude that the model works well in the sense that it identifies relevant and meaningful topics and patterns, including not only topics identified by experts, but also others. All the topics can be interpreted with surprising ease and eleven of the twelve are directly linked with smoking bans.

4.2 Validation

The emergence of frames that public health experts previously identified provides initial and strong validation for our approach and the topics that we have found. Here we further validate the output of the model by considering a few correlations that help us to assess the plausibility of our results.

First, we consider how topics correlate with the timing of smoking ban adoption at the state level. Figure I1 in the appendix 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. 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. This is, again, intuitive, since state legislation often replaces or removes the need for legislative action at the local level (Shipan and Volden, 2006).

Second, Figure I2 shows topic prevalence as a function of the number of months before or after policy adoption at the state level. Again, we recognize a peak for *State legislation* during the month of adoption. We also notice a sharp drop for *Local legislation* at the time of state legislation enactment since, as we just noted, state-wide legislation usually removes the need for legislative action at the local level. During the month of adoption there is also a small peak in *Electoral politics*, which indicates that the views of voters gain relevance at the moment when legislation is passed. Furthermore, we see that *Enforcement* peaks in the first couple of years following policy adoption. Again, this is quite intuitive, as this is the period in which enforcement issues are likely to be more salient. The same trend is visible for *Tobacco companies*, likely in connection with lawsuits or other legal action on their part.

Third, we can check whether states in which restrictions on smoking are more likely to be politically controversial show greater attention to the electoral implications of these laws. 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 I3 shows support for all of these expectations. To begin with, we see that the prevalence of this topic increases as the percentage of smokers in a state goes up. Next, using the share of Democrats in a state's lower house as a rough proxy for the ideological leanings of a state, we find that more conservative states (i.e., those with a lower share of Democrats in the lower chamber) are more likely to focus on electoral implications than more liberal states. Finally, the figure shows that the prevalence of this topic is higher in states with unified Republican control of government than in those with unified Democratic control.

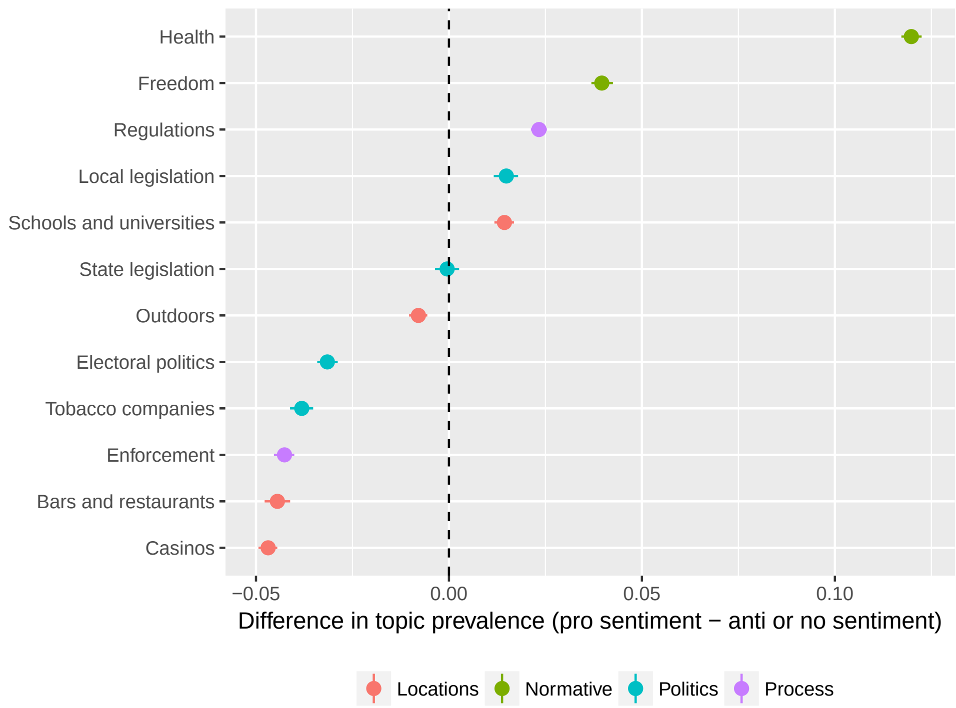

Figure 3: *Topic prevalence and sentiment. "Pro" means that a paragraph reports facts or opinions that emphasize the success of, or need for, smoking restrictions. "Anti" denotes paragraphs conveying facts or opinions that highlight potential problems associated with smoking restrictions.*

Taken together, our results show that the role of voters is discussed much more frequently in states where voters are likely to be less receptive to smoking bans, either for ideological or partisan reasons or because the policy is likely to affect the lifestyle of many people.

Fourth, as discussed earlier, we also coded the sentiment of each topic—that is, whether the article 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 within the *Locations* category—*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 3 showing the *Health* topic exhibiting the most positive sentiments and *Bars* *and restaurants*, *Casinos*, and *Enforcement* exhibiting the most negative sentiments.[16]

4.3 Policy Diffusion and Policy Frames

The main question that we seek to address in this paper is whether and how the way an issue is defined (or framed) within a state is related to the presence or absence of adoptions within that state's diffusion network. Figure 4 provides direct evidence of this phenomenon.

Our findings indicate that the prevalence of some topics does indeed vary as a function of prior policy adoptions within the diffusion network. We begin by focusing on topics that fall within the category of *Locations*—that is, topics related to smoking bans in specific establishments or areas. The correlation 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 or bans regularly raise concerns about the potentially harmful economic effects of such policies on bars and restaurants (Warner, 2000), which is reflected in the negative sentiment discussed in Section 4.2. Analysis of the effects of bans on bars and restaurants has not, however, produced consistent evidence that such concerns are warranted. Although some studies do find negative effects, at least for bars (Adams and Cotti, 2007, for example), many others find instead that smoking restrictions have either a beneficial effect, or no effect, on these establishments (Warner, 2000; Scollo et al., 2003). Indeed, as Tomlin (2009, 1) asserts, "With a few exceptions, these studies conclude that smoking bans have no economic effects or positive economic effects" on the hospitality industry.

We see the opposite effect for the topic *Casinos*. Like *Bars and restaurants*, the sentiment of this topic is markedly more negative than positive. But unlike *Bars and restaurants*, the topic 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. A key difference between these two types of laws is that studies of the economic effects of smoking restrictions on casinos have not produced a consensus of positive (or even null) effects; instead, studies often have concluded that such laws have been harmful to casinos (e.g., Garrett and Pakko, 2010; Thalheimer and Ali, 2008). These findings connect directly with the idea of policy learning, namely, that beliefs about the consequence of a policy (i.e., whether it harms business or not) are updated based on what is observed elsewhere.

[16]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.

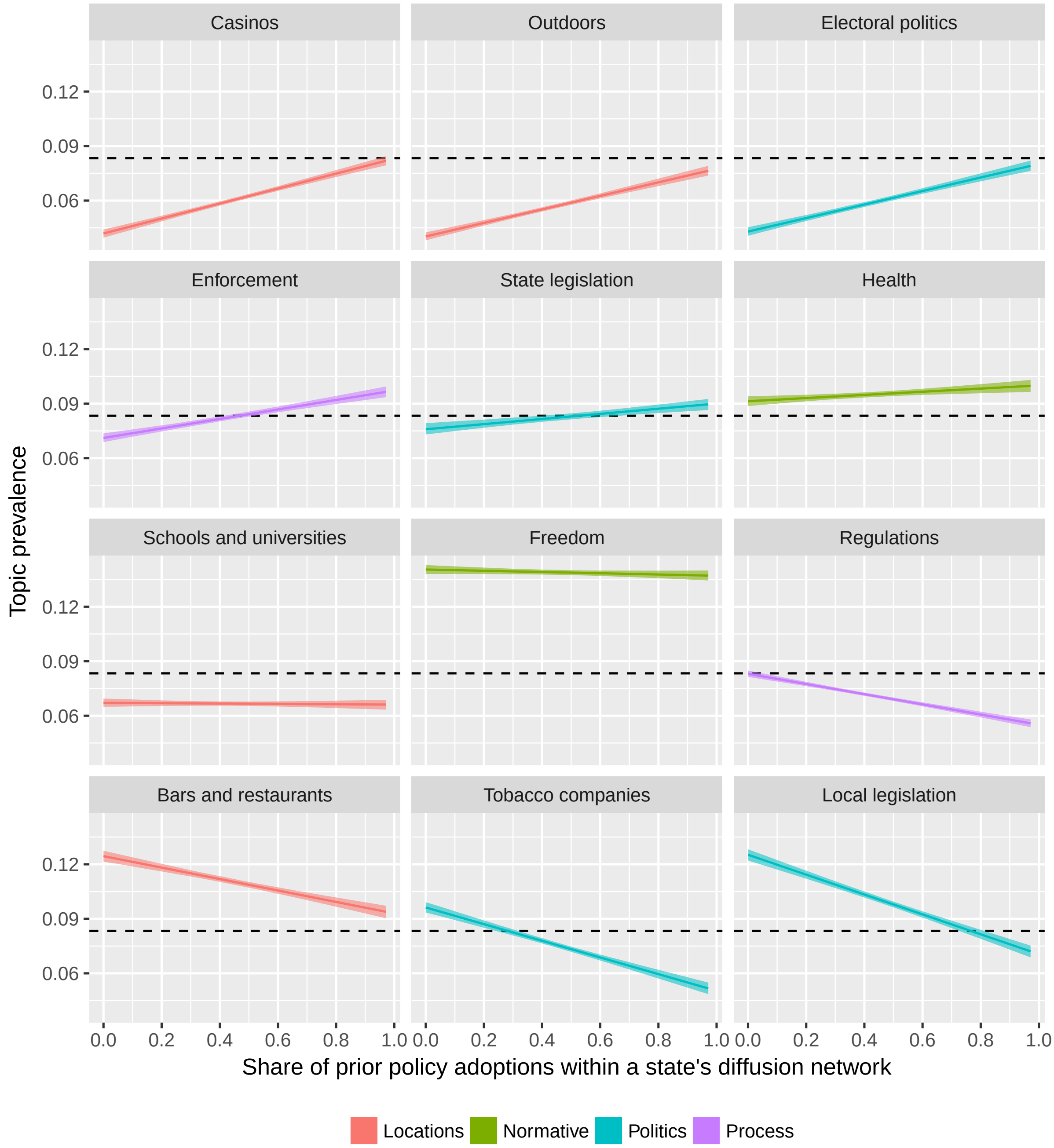

Figure 4: *Topic prevalence co-varies with the share of prior policy adoptions within a state's diffusion network. The horizontal line shows baseline topic prevalence across all twelve topics. Topics are sorted by decreasing correlation.*

With bars and restaurants, we see that as more states adopt laws, and as more evidence comes out that such laws are not harmful to these types of establishments, this topic is less likely to emerge as a policy frame. With casinos, on the other hand, as more states adopt laws, and as evidence begins to amass that points to potential harmful consequences, the topic is more likely to emerge as a frame.[17]

Our findings for topics in the *Locations* category indicate that states are likely to learn from adoptions by other states in their diffusion network. But learning is not just about policy outcomes; it is also about political outcomes and activities, which are captured by topics in our *Politics* category. Figure 4 shows that one 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, 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 when the policy becomes more widespread. As a result, these states see less need to focus on or defer to this group.

A second topic in this category, *Electoral politics*, identifies voters' involvement in the decision-making process, and more generally the political-electoral dimension of smoking ban adoption and implementation. The topic's prevalence increases when smoking bans become more widespread within the diffusion network. When no other states within the network have enacted smoking bans, voters' views receive little attention. However, electoral politics becomes a much more prominent topic when states within the diffusion network start to pass smoking restrictions. Since the sentiment of this topic is on balance more negative than positive, as shown in Figure 3, this result implies that new information on possible voter resistance to smoking restrictions diffuses across states. Another important correlation in the political group, 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. The positive, though quite small, correlation with *State legislation* supports this interpretation.

Turning to our *Process* category, which includes topics related to the practical aspects of smoking

[17] As Garrett and Pakko (2010) also point out, the potential harmful effects to casinos are likely to generate sharp debate, given that the marginal effect of casinos on local employment and tax revenues is likely to be much greater than that of a bar or restaurant, and a ban on smoking in casinos is likely to have a stronger effect than a similar ban in restaurants or bars because people tend to spend longer periods of time in casinos.

bans, a significant correlation is apparent for *Regulations*. This topic identifies the technical aspects of smoking bans, such as rules or permits for separate smoking areas, ventilation, exemptions, and so on. Getting these regulations right is important for the implementation of smoking bans, as uncertainty surrounding them may worry business owners. Figure 4 shows that these issues are quite salient when no other state within the diffusion network has enacted smoking bans, and much less so when many have. As with *Bars and restaurants* or *Casinos*, this finding suggests that the experiences of other states are used to update prior 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. Like *Casinos*, this topic tends to have a negative sentiment; hence, its salience increases as more evidence from states within the diffusion network becomes available, showing that the enforcement of smoking bans is not always unproblematic.

Not all topics are correlated with the policies of other states. Most notably, the topics that we have categorized as *Normative* do not show evidence of such correlation. 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—it is the most frequent topic—but its relevance does not increase or decrease when more states within the diffusion network adopt the policy. That is, the experiences of other states do not change the frequency 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 as a function of earlier adoptions (although unlike *Freedom* there is evidence of a very slight increase). This finding is not surprising, given that the effects of smoking restrictions on health are rather mechanical. That is, these effects are tied to broader events, such as the Surgeon General's statements on smoking or the Environmental Protection Agency's evaluation of the effects of secondhand smoke, and thus are not something where opinions are likely to change much based on the experiences of other states. This is precisely what we see.

We conclude that the way smoking bans are framed changes depending on the prevalence of the policy within a state's diffusion network. 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 of smoking bans for bars and restaurants, the influence of tobacco companies, and regulatory details) become less relevant.

And still others—namely, those that capture normative aspects of the debates over this policy area—are unaffected by earlier adoptions.

5 Discussion and Conclusion

Policy diffusion is the process by which policymaking activity in one government is influenced by activity in other governments. Our study is firmly embedded within the literature on policy diffusion, but it brings a new perspective. Drawing on studies of the life cycle of the policymaking process, which have highlighted the crucial importance of the issue definition stage, we have focused on framing and issue definition within the context of diffusion. Rather than examining whether policy adoptions are a function of previous adoptions by earlier-acting states, 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.

We conducted our analysis using structural topic models, which is a new approach in the diffusion literature. Drawing on an initial dataset of more than 3 million paragraphs that appeared in 49 newspapers covering 49 states, we first identified which of these paragraphs focused specifically on anti-smoking laws. Next we used a structural topic model to identify the ways in which this issue was framed, then showed that these frames, or topics, varied with the frequency of earlier adoptions by states within the diffusion network. Doing so allows us to develop and present the first examination of whether and how the initial stage of the policymaking process—when issues are first being defined and framed—is linked to prior adoptions.

Our approach produces several contributions along multiple dimensions. At a descriptive level, we provide a more thorough understanding of a specific policy area—here, restrictions on smoking. Our structural topic model identifies the various ways in which this issue has been framed, and the results of our analysis are consistent with earlier, smaller scale studies of issue definition in this policy area. However, by analyzing the issue on a much broader scale—in terms of the number of governmental units, years, and sources—we are able to show which frames appear most frequently, which have been stable (in terms of their prevalence) over time, and which have become either more or less common.

But our analysis goes well beyond contributing to our understanding of issue definition within one specific policy area. We show that issue definition is an integral part of the diffusion process, one that future studies of diffusion should take into account. Most notably, we find that as a policy becomes more widespread within the diffusion network, the ways in which the issue is defined changes, although this connection does not exist for all types of frames. Normative rationales of a policy are relatively unaffected by previous adoptions. More practical aspects, on the other hand, 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.

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.

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 obviously 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 easily be 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 diffusion perspective—one showing how policymaking activities in previous and current states are related—might be highly relevant. The approach we have used, both in terms of focusing on the issue definition stage and in terms of using large amounts of data related to this stage, shows how scholars can study any policy or other political phenomena from a diffusion angle, regardless of whether policies have been adopted. Policy ideas can spread from one state (or country) to another, even if the process does not culminate in the adoption of a new law.

Our analysis sets the stage for the examination of an additional set of theoretical 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 policy adoptions as covariates, we cannot include the prevalence of earlier frames within a stateâĂŹs diffusion 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, in this paper we have assessed sentiment as a way to further validate our use of structural topic models, a function it performs well. However, combined with frames, sentiment also could be seen as an integral part of issue definition. Combining topics and sentiment in a coherent outcome variable is not straightforward within our methodological approach because while sentiment is measured prior to the analysis, topics are not—they are identified inductively together with their correlation with covariates. Future studies should work to develop new ways to assess the link between sentiment and framing as a measure of issue definition.

Furthermore, now that we have established the connection between earlier adoptions and how issues are later defined, and demonstrated the usefulness of using large amounts of data to study this connection, new studies can attempt to pin down additional aspects of diffusion. For example, it will be worthwhile to examine the specific conditions under which ideas diffuse from prior adoptions to issue definition, how the multidimensionality of a policy (and in particular normative versus practical frames) affects this diffusion, and the role that various mechanisms of diffusion play in this process.

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 start 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.

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Appendix

A Newspaper corpus

Newspaper	*State*	*Articles*	*Paragraphs*	*Filtered*
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[a]	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[a]	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[a]	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[a,b]	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[a]	LA	3,600	17,776	90
Topeka Capital-Journal	KS	5,976	32294	564
Union Leader[a]	NH	975	3,944	43
Wilmington Star-News	NC	6,863	34,211	515
Wyoming Tribune Eagle	WY	2,024	13,526	769
Total		560,229	3,159,350	52,675

[a] Several years of coverage could not be retrieved due to access restrictions.
[b] Documents retrieved with a simplified keyword search string, since it was only available in one specific database.

Table A1: *Newspaper corpus.*

B Newspaper articles retrieval

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.

C 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.

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 C1: *Evaluation of crowd coding.*

For establishing a development set for the classification of paragraphs into relevant or irrelevant 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 Crowdflower.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 rcowd 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.

D 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[18] of 0.80 or higher—a further sign of the consistency and thus reliability of the classification (Collingwood and Wilkerson, 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 D1: *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.*

[18]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.

E Topic model coherence and discrimination

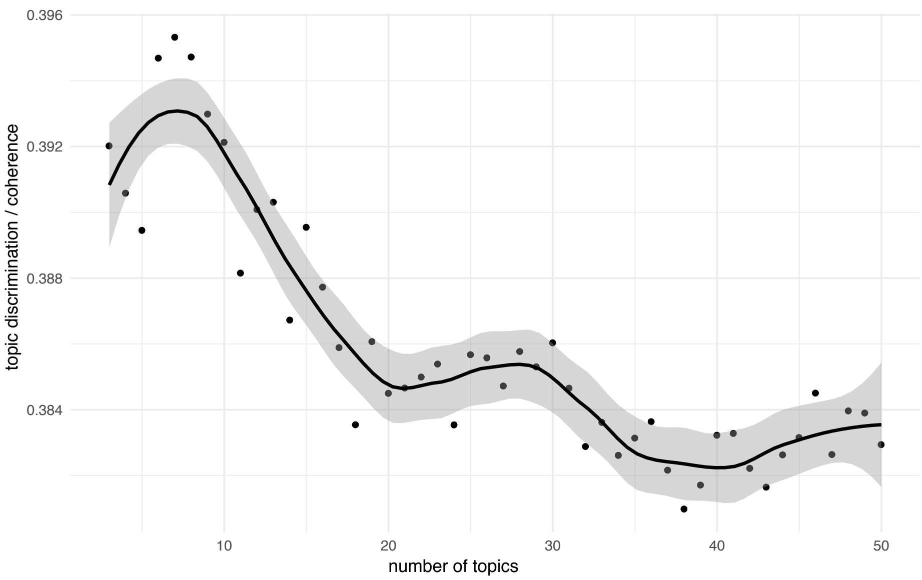

Figure E1: *Word2vec topic coherence and discrimination averages for varying numbers of topics.*

For this evaluation, the word2vec topic coherence and discrimination is calculated as follows. Let $T = t_1, \ldots t_K$ be the K topics estimated by a model and $t_i = [w_{i1}, \ldots w_{iP}]$ a vector of P top ranked words that characterize each topic. In addition, let $w_{ij} = [d_{i1}, \ldots d_{iD}]$ 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 α, which is set to 0.3 in our case:

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

F Results of alternative topic models

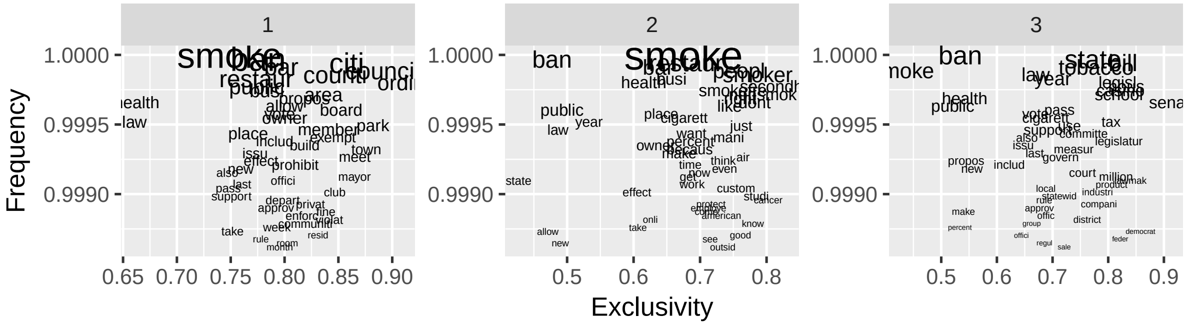

Figure F1: *Top-50 words for the three topic model.*

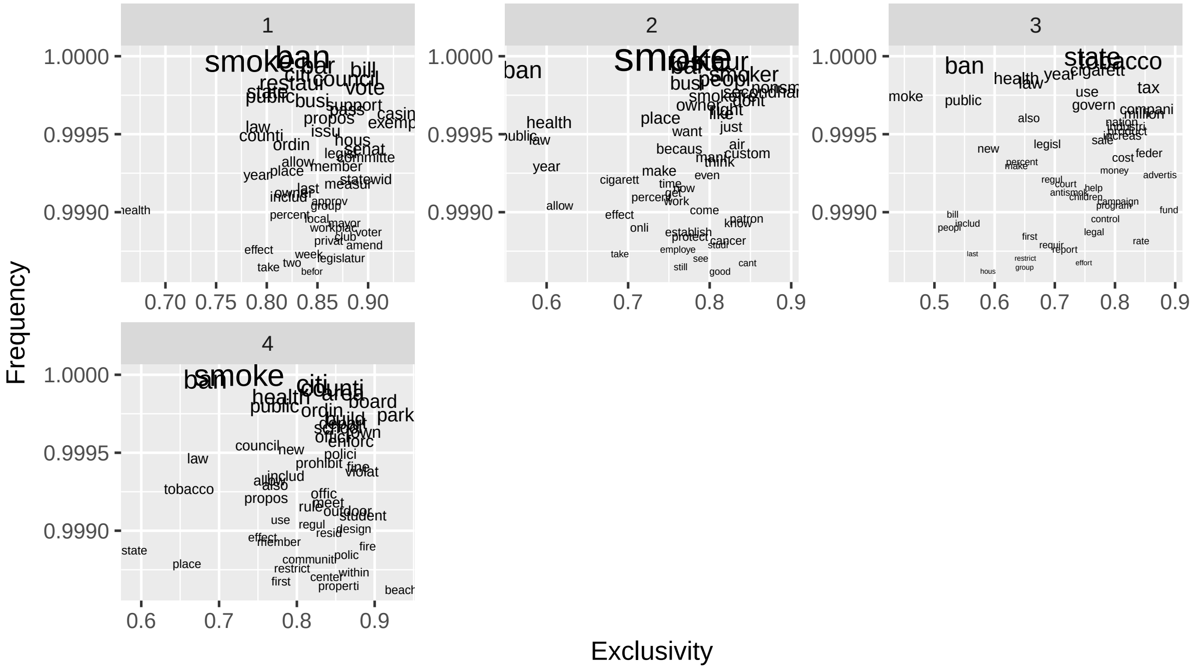

Figure F2: *Top-50 words for the four topic model.*

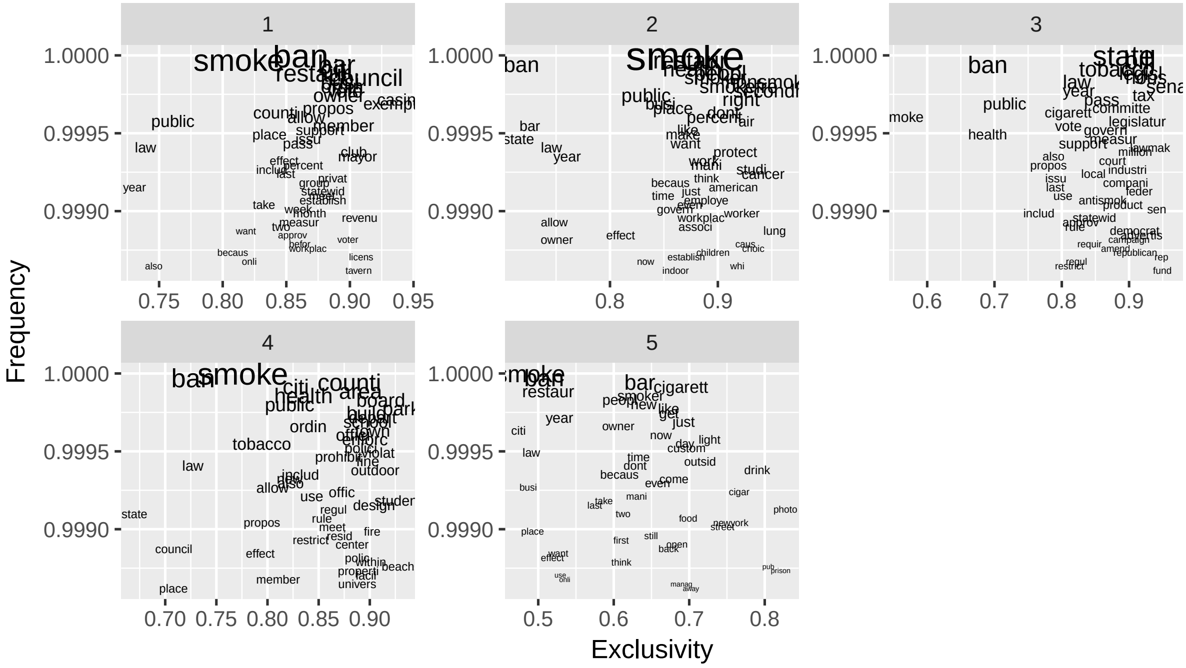

Figure F3: *Top-50 words for the five topic model.*

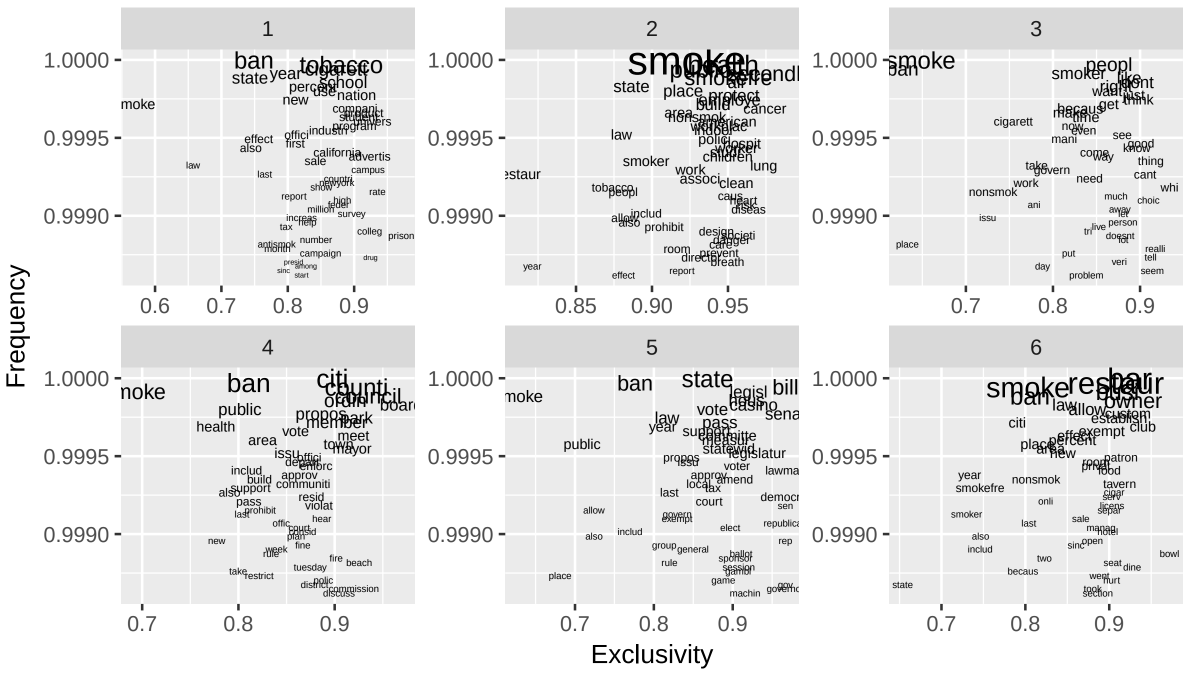

Figure F4: *Top-50 words for the six topic model.*

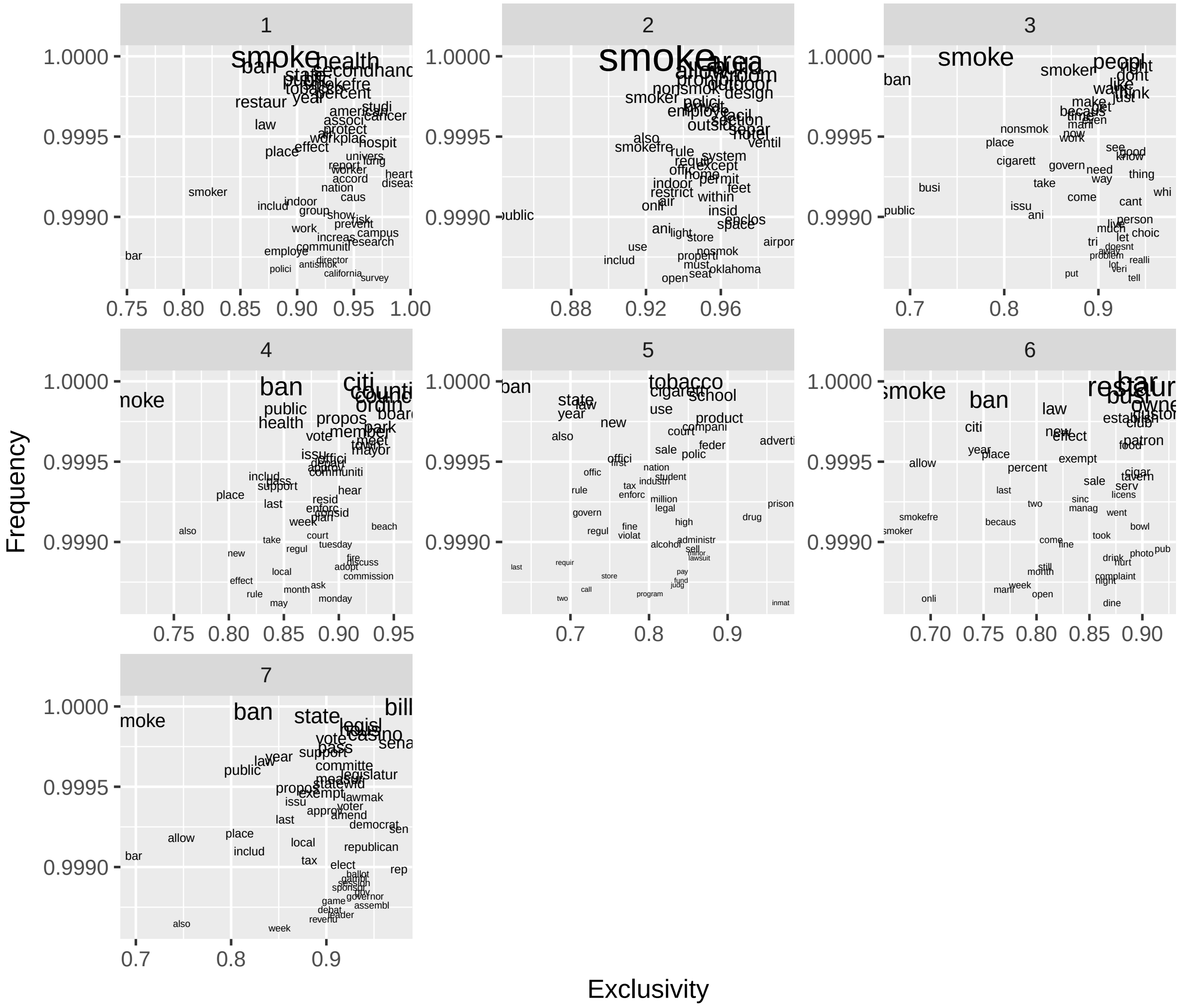

Figure F5: *Top-50 words for the seven topic model.*

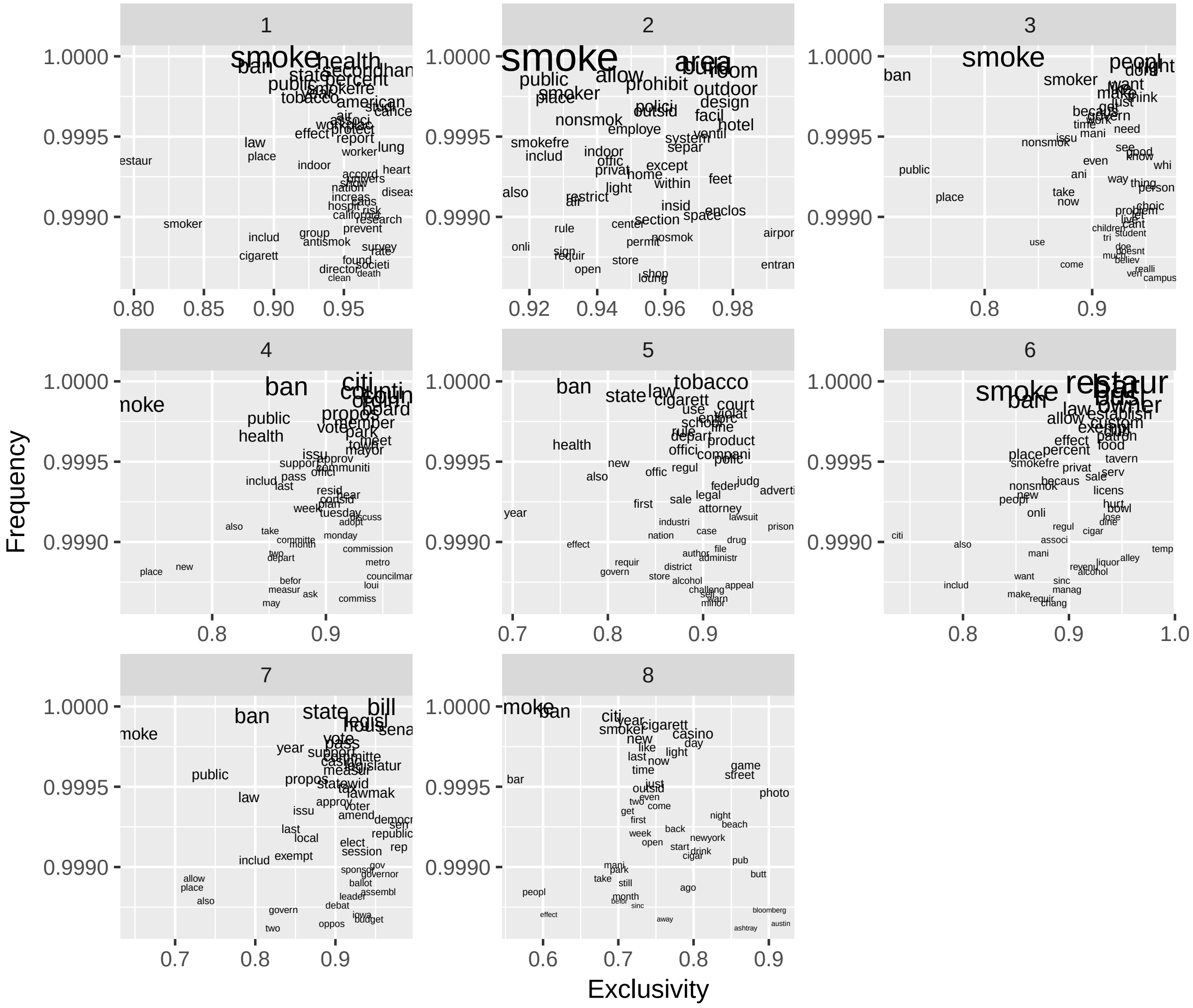

Figure F6: *Top-50 words for the eight topic model.*

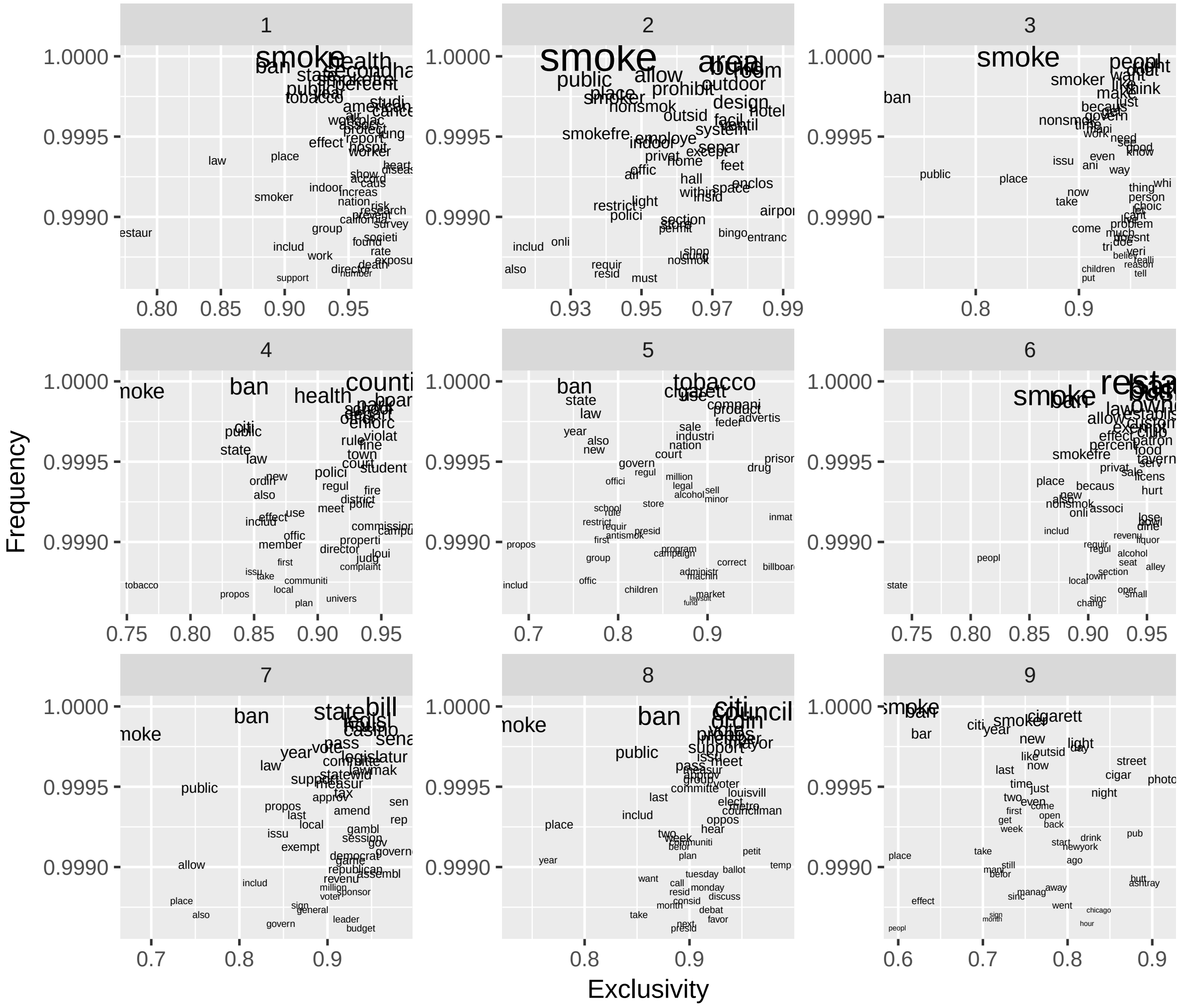

Figure F7: *Top-50 words for the nine topic model.*

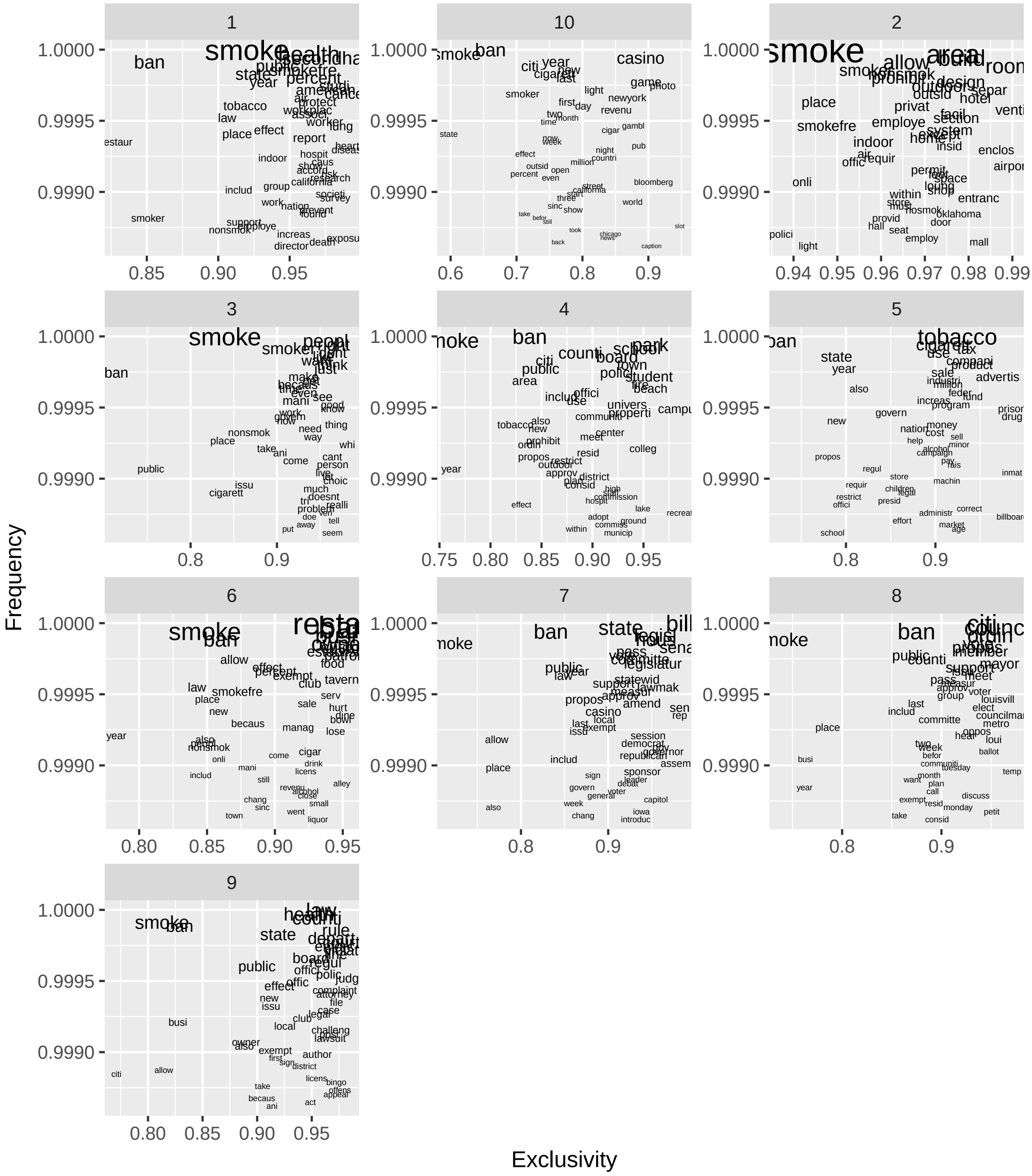

Figure F8: *Top-50 words for the ten topic model.*

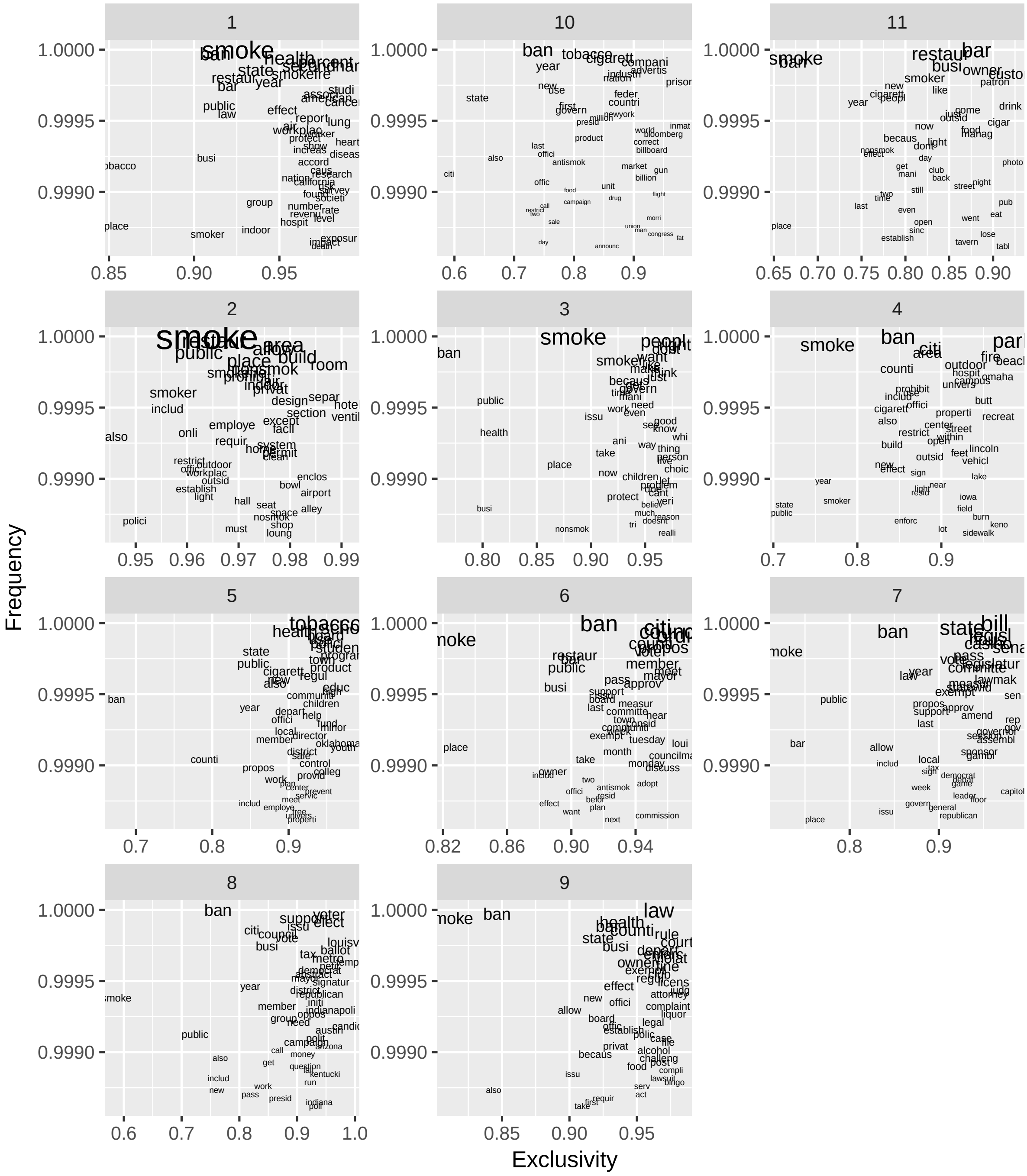

Figure F9: *Top-50 words for the eleven topic model.*

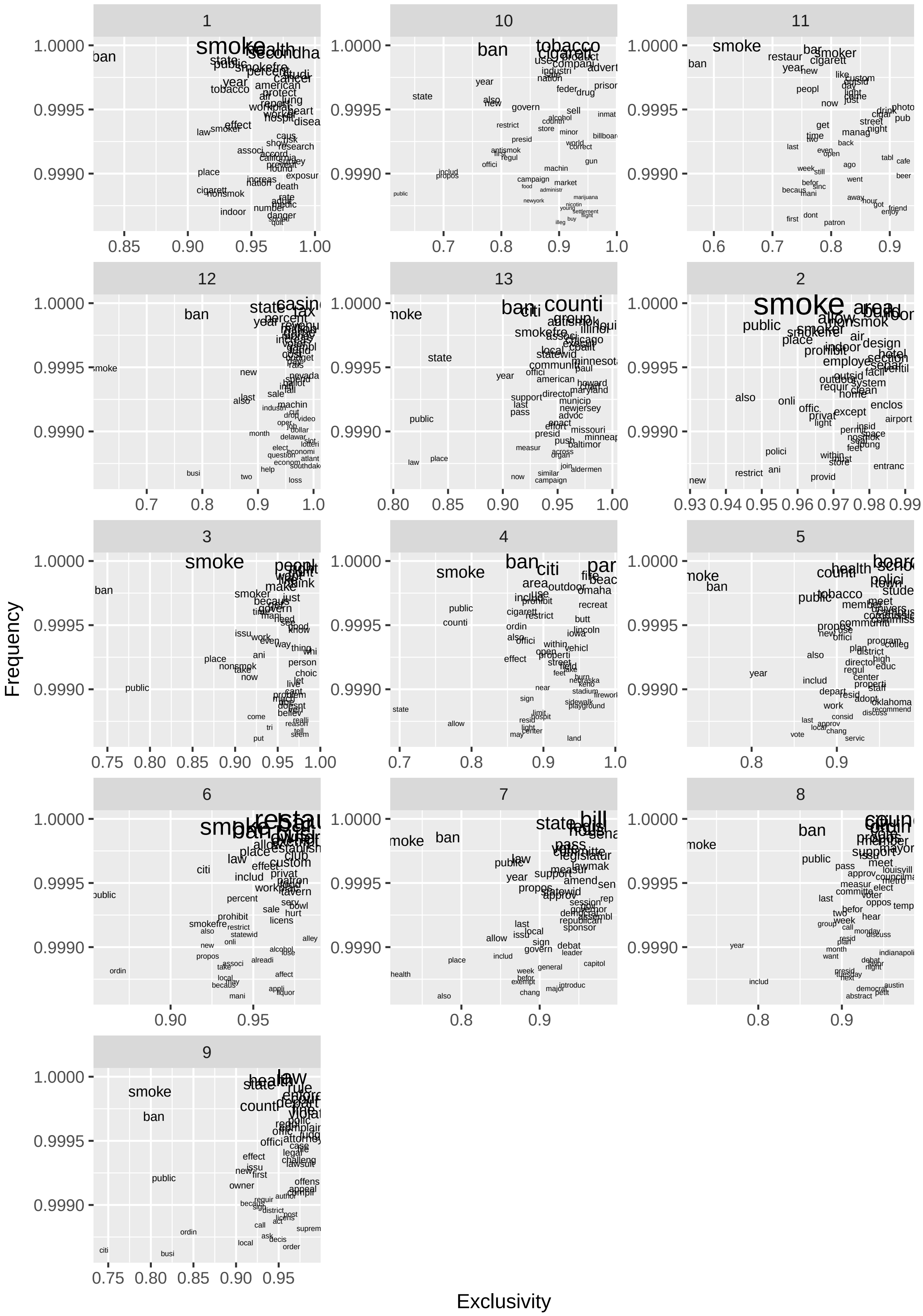

Figure F10: *Top-50 words for the thirteen topic model.*

G Extrapolation of diffusion networks

The binary diffusion ties in the policy diffusion networks in Desmarais, Harden and Boehmke (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

H Representative paragraphs per topic

Table H1: *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.*

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.
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.
Regulations
Rule highlights: - Required restaurants, bars, pool halls, bingo halls and bowling alleys to be designated as entirely smoking 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.
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
Freedom
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.

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.

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.

Schools and universities

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 spokeswomen 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.

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.

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.

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.

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.

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.

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.

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.

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.

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.

Tobacco companies

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.

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.

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

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.

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.

I Validation

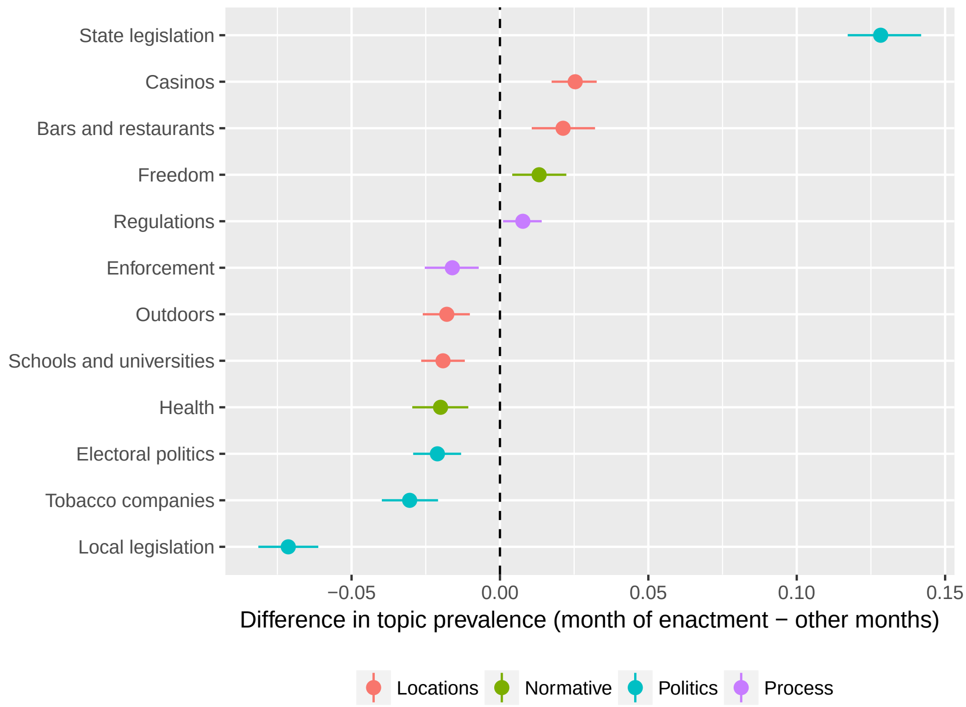

Figure I1: *Topic prevalence as a function of policy adoption at the state level in a given month.*

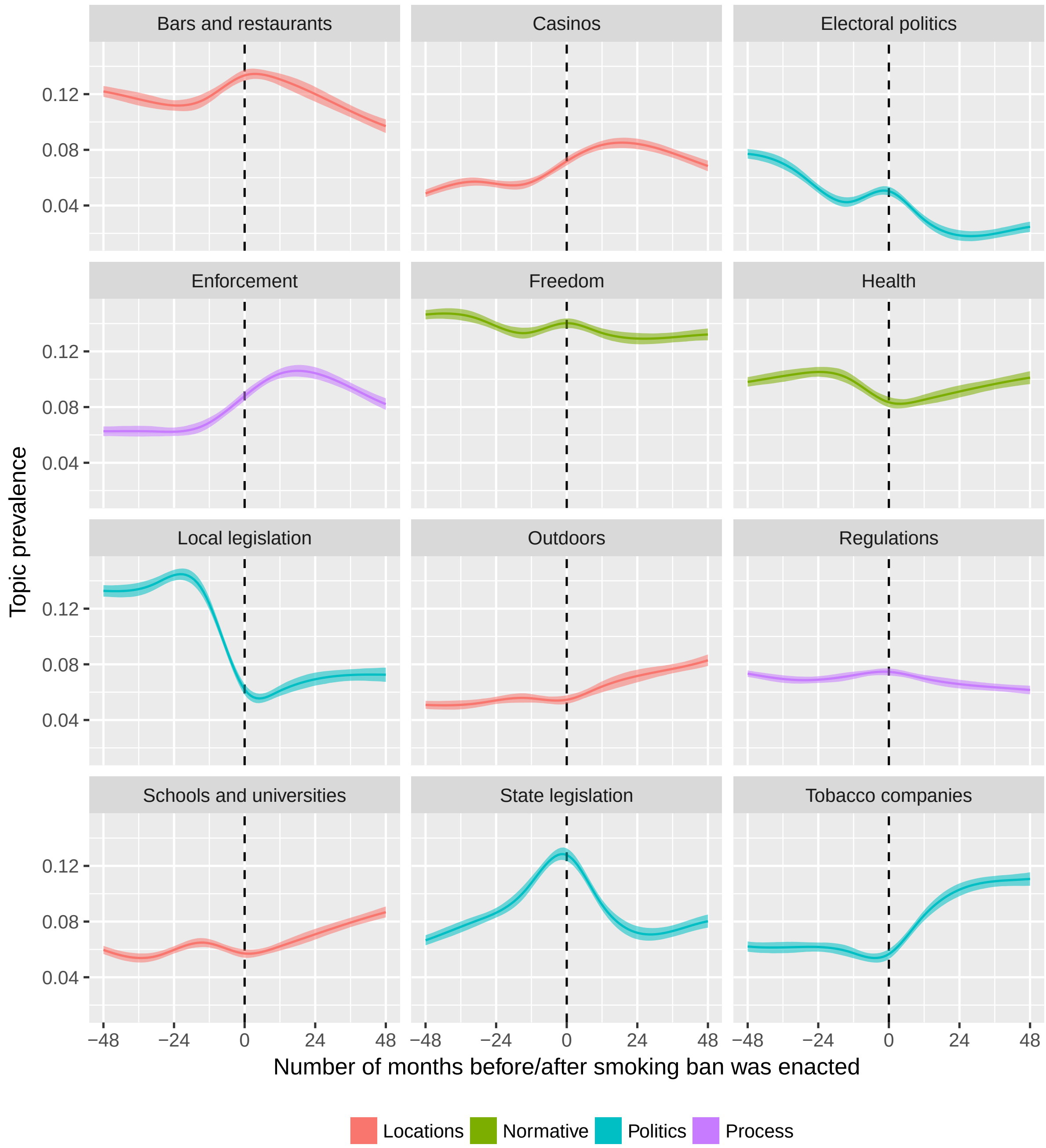

Figure I2: *Topic prevalence as a function of the number of months prior to or since policy adoption at the state level.*

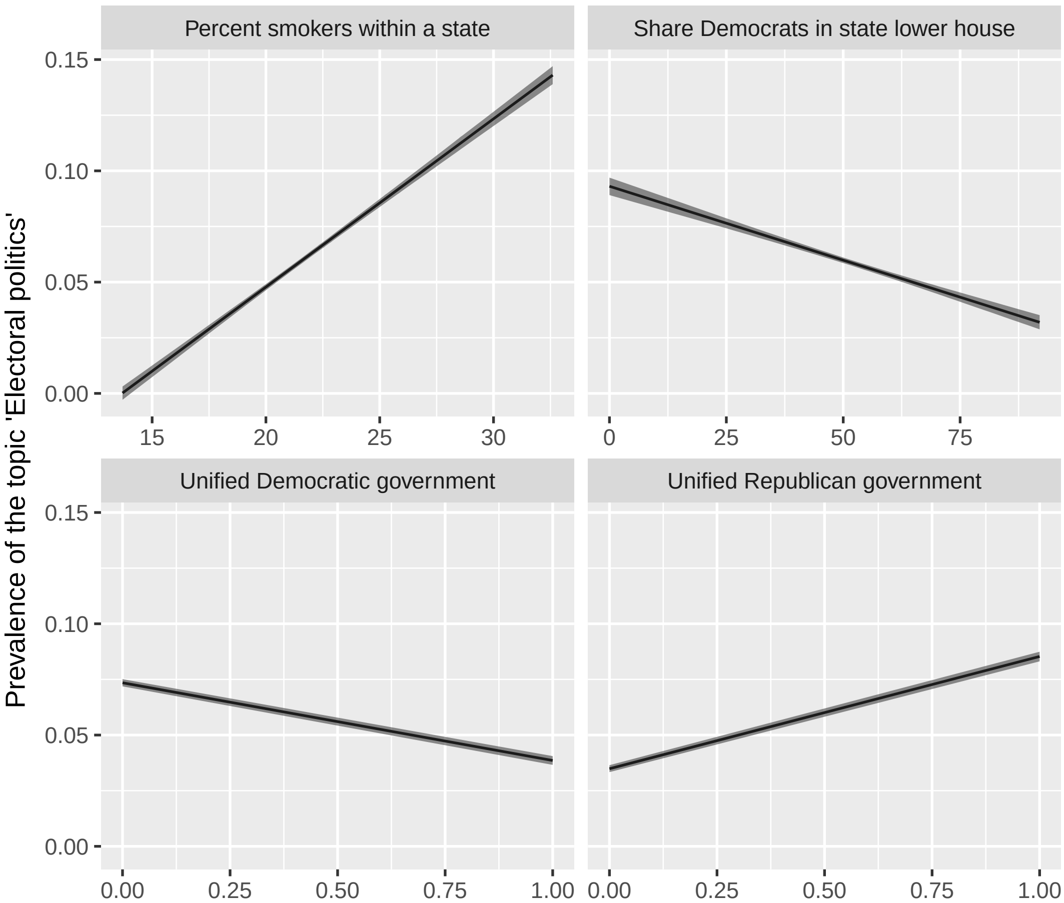

Figure I3: *Prevalence of the topic* Electoral politics *as a function of four variables.*