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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 topic models to estimate how policies are framed during this stage and how these frames are predicted by prior policy adoptions. Focusing on smoking restriction in U.S. states, our analysis draws upon an original data set of over 52,000 paragraphs from newspapers covering 49 states between 1996 and 2013. We find that frames regarding the policy's concrete implications are predicted by prior adoptions in other states, whereas frames regarding its normative justifications are not. Our approach and findings open the way for a new perspective to studying policy diffusion in many different areas.*

Verification Materials: The data and materials required to verify the computational reproducibility of the results, procedures, and analyses in this article are available on the *American Journal of Political Science* Dataverse within the Harvard Dataverse Network, at https://doi.org/10.7910/DVN/QEMNP1.

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

In this article, we examine whether and how prior adoptions predict the way an issue is defined, or framed, in other states.[1] Learning about this connection is crucial to a deeper understanding of policy diffusion, as policy ideas can spread from one government to another even if this diffusion does not result in an adoption. Adoptions are rare, whereas consideration of new policies occurs frequently; and issues can be defined in a variety of ways. To this end, in our analysis we treat issue definition as an outcome and examine whether and how previous policy adoptions predict how an issue is later defined.[2]

We use structural topic models (Roberts, Stewart, and Airoldi 2016) to estimate how policies are defined. Applying this technique to an original data set of 52,000 newspaper paragraphs about anti-smoking laws in the U.S. states reveals how this issue has been defined and

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[1]We use the terms *issue definition* and *policy framing* interchangeably.

[2]In other words, we analyze policy-to-frame diffusion, not frame-to-frame diffusion. We elaborate on this point in the conclusion.

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how this framing has evolved. Based on this approach, we analyze whether the prevalence of these issue definitions is predicted by earlier policy adoptions.

Our theoretical and empirical analysis proceeds in two steps. First, controlling for many other relevant factors, we find that some frames used to describe smoking restrictions in a given state are predicted by the prevalence of policy adoptions in other relevant states.

In analyzing this relationship, we draw upon theoretical studies regarding the mechanisms of diffusion to understand why some issue definitions are subject to diffusion, whereas others are not (Braun and Gilardi 2006; Shipan and Volden 2008; Simmons, Dobbin, and Garrett 2006). In particular, we examine expectations related to two mechanisms: learning and emulation. We find that issue definitions are predicted by prior adoptions in topics where learning can occur, that is, in topics that refer to concrete, observable aspects of the policy. In contrast, when we examine the mechanism of emulation, we find that the most prominent normative frame—individual rights—is not predicted by prior adoptions.

Second, after demonstrating the connection between issue definition and prior adoptions, including the role of diffusion mechanisms, we explore whether individual definitions occur in combination with each other. Our initial analysis considers individual topics, as these constitute "the smallest units of framing" (Baumgartner, De Boef, and Boydstun 2008, 107). But in addition to allowing us to identify simple frames, individual topics also can serve as building blocks, with topics combining to create more complex definitions. Our approach allows us to determine which topics occur together, giving us insight into how and when complex frames occur. The results show that the complexity of definitions increases as the policy becomes more widespread.

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

Theoretical Background

Policy Diffusion and Issue Definition

We situate our study directly within the literature on diffusion. Most studies of diffusion have focused on policy adoptions as both an independent variable and a dependent variable—that is, whether earlier policy adoptions influence the likelihood of later policy adoptions (e.g., Berry and Berry 1990; Boehmke and Witmer 2004). Yet such an approach can lead to pro-innovation bias, which is a tendency to focus on the adoption of innovations to the exclusion of other potentially significant features of diffusion and policymaking, thereby depriving us of a broader understanding of these processes (Karch et al. 2016; Rogers 2003). We address a specific form of this bias: Although it is well recognized that policies pass through several stages before reaching the adoption stage, few diffusion studies have considered the relationship between prior adoptions and these earlier stages (Gilardi and Wasserfallen 2019).[3]

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

Although there are countless studies of issue definition, from the standpoint of diffusion Boushey's (2016) innovative investigation of the adoption of criminal justice policies is the closest to ours, in that he examines the importance of issue definition within a policy diffusion framework. However, our study and his have opposite explanatory concerns: He examines how the definition

[3]Karch (2007) focuses on agenda setting and information generation, Pacheco (2012) on public opinion, and Pacheco and Boushey (2014) on the political agenda. Other studies consider later stages, such as implementation (Nicholson-Crotty and Carley 2016) and post-adoption modifications (Karch and Cravens 2014).

(more specifically, the social construction) of an issue affects its diffusion, but we focus on how diffusion can produce different issue definitions over time and across governments. Thus, our study and his are complementary, with Boushey examining how frames can lead to adoptions, whereas we investigate how adoptions can predict frames.

Issue Definition and Policy Frames

Policy frames can be defined as "the presentation or discussion of an issue from a particular viewpoint to the exclusion of alternate viewpoints" (Baumgartner, De Boef, and Boydstun 2008, 106). In other words, these frames or *issue definitions* tell us how a policy problem is perceived or understood at any given time (Baumgartner and Jones 1993). Because policies are usually multidimensional, it is neither automatic nor obvious that a policy will be defined in a particular way, or that this frame will remain constant over time. Instead, we argue that these frames can be predicted by earlier actions taken by other states.

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

These definitions and changing narratives can have important implications and downstream effects. Changes in issue definitions and frames can, for example, lead to shifts in the agenda (Kingdon 1984). Issue definition also can affect how policy alternatives are designed during the formulation stage of the policy process (Wildavsky 1987). How an issue is defined can influence policy outcomes, as Baumgartner, De Boef, and Boydstun (2008) demonstrated by showing that changes over time in the framing of the death penalty produced shifts in both public opinion and policy outcomes (measured by the frequency of death sentences). More generally, changes in issue definition can lead to the punctuation of policy equilibria (Baumgartner and Jones 1993). Overall, the effect of issue definition on later stages in the policymaking process, including adoption, is "nearly axiomatic" within the policymaking literature (Boushey 2016, 200).[4]

As we will discuss later, our approach identifies frames empirically using topic models, which means that we consider the topics uncovered by these models as an operationalization of policy frames. We follow DiMaggio, Nag, and Blei (2013, 578, 593), who convincingly argue that topic models are an ideal tool for identifying frames in texts: "Many topics may be viewed as *frames* . . . and employed accordingly [. . .] [T]opic modeling has some decisive advantages for rendering operational the idea of 'frame.'" Such topics can be used individually to show simple frames or can be combined to show larger and more complex frames (Baumgartner, De Boef, and Boydstun 2008). From the analyst's perspective, "[i]n specifying issue-frames, one can aggregate or disaggregate subframes" (Gamson et al. 1992, 385). Our analysis does both.

In the next section, our theoretical analysis outlines the logic for why a diffusion process might link earlier adoptions and later frames, considering both individual frames (or subframes) and more complex frames. First, we focus on individual frames and elaborate predictions about the relationship between prior adoptions and these frames. Second, because individual frames form building blocks from which more complex frames might be constructed, we then turn our attention to the potential for connections across them.

Theoretical Expectations

We argue that the diffusion process might occur between earlier adoptions and later frames by building on the logic scholars have used to explain adoption-to-adoption diffusion. If a state has not yet adopted a policy, political actors in that state will look to see what other states have done. They will observe which states have adopted policies and which have not. They will note which aspects or dimensions of policies have been emphasized in prior laws. They will discern how the politics played out in these earlier states—for example, which groups were satisfied, which were not; whether there was public support; and so on. Moreover, they will perceive which approaches these other states have taken, whether these approaches were successful, and whether these approaches would be

[4]Other notable studies of framing examine immigration (Haynes, Merolla, and Ramakrishnan 2016), agriculture (Bosso 2017), birth control (VanSickle-Ward and Wallsten 2019), and tobacco policies (e.g., Menashe and Siegel 1998).

appropriate for their own states. In other words, they will observe the politics and policy implications surrounding earlier adoptions. They can then use this information to try to define the issue in a specific way in their own state since, as we have established, these definitions have implications for later stages of the policy process, they are malleable, and they can change over time.

Of course, it is possible—and a common assumption in most of the diffusion literature—that not all other states will matter equally. That is, when considering how a policy is framed in a state that is newly considering a policy, prior adoptions in one set of states might affect this framing, whereas prior adoptions in another set of states might not. Although there are multiple ways to capture the influence of other states, in our empirical analysis we will focus on one way, utilizing Desmarais, Harden, and Boehmke's (2015) identification of a state's diffusion network, but we will also report results based on using other sets of states. For now, we remain agnostic about which set of states will matter, asserting more generally that policy adoptions in other relevant states can influence issue definition. Our first expectation highlights this relationship:

Hypothesis 1 (Diffusion): Prior adoptions by other relevant states predict the prevalence of policy frames within a state.

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

Here, we focus on two of these mechanisms: learning and emulation. Much of our earlier discussion about what political actors would observe from policy adoptions in earlier states can be interpreted as learning (Gilardi 2010; Shipan and Volden 2014; Volden 2006). They might, for example, learn about the politics of how a policy played out in other states (e.g., which groups were happy with the adoptions, whether public reaction was positive, or whether the issue affected electoral outcomes). And they might also learn about policy implications, such as whether the policy worked, who it benefited, and more.

If the connection between earlier adoptions and later issue definitions is based on learning about the practical consequences of adoption, then we would expect to see specific changes in how issues are defined over time. In other words, experiences can shape frames, causing these frames to either increase or decrease in importance. In particular, there are several dimensions of anti-smoking policies where learning about consequences is likely to take place—most notably, those that are practical or concrete enough for the law's consequences to be observed with relative ease.

The effects of these laws on bars and restaurants are cases in point: One can fairly easily assess evidence on whether these businesses struggle or thrive in the aftermath of smoking bans. More specifically, in the aftermath of the adoption of restrictions on smoking in restaurants and bars, there was little evidence of overall economic harm to these industries. To the extent that later states learned from the experiences of these earlier states, we would expect these particular frames to recede in importance. Health is another aspect that is potentially linked to learning, although not unambiguously. On the one hand, policy makers may observe aggregate health outcomes in states that have adopted smoking bans and update their beliefs on the usefulness and effectiveness of this policy. On the other hand, much of this learning occurred prior to the period we examine, via landmark reports about the negative health consequences of smoking and secondhand smoke, so new adoptions arguably had a limited ability to contribute new knowledge about the health consequences of smoking.

In general, then, if states learn from prior adoptions, we would expect these particular topics or frames to be related to earlier adoptions, as the frequency of the topic will change based on the learning that occurs. Political actors will learn about the consequences of adoptions, and this knowledge will be reflected by the frequency of a topic changing as a result of earlier adoptions. We state this expectation as follows:

Hypothesis 2 (Learning): Prior adoptions by other relevant states predict the prevalence of policy frames that are based on practical, empirically verifiable consequences.

States also can emulate actions taken by other states. In a diffusion context, emulation occurs when one state follows the lead of an earlier state because its action is normatively appealing (Braun and Gilardi 2006; Simmons, Dobbin, and Garrett 2006). This normative appeal in turn stems from socially constructed aspects of policies—in particular, whether these policies are viewed as being appropriate, whether they have broad support, and whether their adoption confers legitimacy upon the adopter (Meyer and Rowan 1977; Walker 1969). This stands in contrast to the learning that can occur about empirically observable consequences of policies. Of central importance is the argument, developed by Finnemore and Sikkink (1998), that when a normatively appealing idea or frame becomes common and widely accepted, it becomes internalized by political actors. When that happens, this idea becomes progressively taken for granted, until it is "no longer a matter of broad public debate" (Finnemore and Sikkink 1998, 895). Consequently, as more states adopt policies, the frame should fade from view and be invoked less frequently.

One potential anti-smoking frame stands out as having a strong normative component: freedom, or individual rights. There is little potential for learning about this topic from prior adoptions. States do not learn about individual rights from earlier anti-smoking laws in the same way they can observe the consequences of such laws for bars and restaurants. On the contrary, this frame represents an aspect of the policy that has become widely accepted, internalized, and taken for granted by policy makers. Polls revealed that a very high proportion of the public consistently believes that smoking should remain legal, implying freedom *to* smoke, while also supporting smoking restrictions in public places, implying freedom *from* smoke.[5] Because these views are now taken for granted, with the public learning little from prior adoptions about the right to smoke or to be protected from smoke, debate will increasingly take place over other aspects of the policy.[6] A frame with a strong normative component has little potential for learning. We thus expect the frequency of a normative frame to decrease with the incidence of smoking bans, as other issues rise to the fore. This leads to our third expectation:

Hypothesis 3 (Emulation): There is a negative correlation between policy adoption by other relevant states and the prevalence of frames based on normative arguments.

So far, we have concentrated on individual frames—appropriately so, since a necessary step toward understanding the links between prior adoptions and frames, as well as the mechanisms undergirding these links, requires first a clear assessment of individual frames. As stated earlier, we view individual topics as building blocks that can stand on their own. However, it is also possible—even likely—that these simple frames can combine to create more complex frames. Indeed, as discussed in the previous section, prior theoretical work maintains that individual frames can be aggregated (e.g., Gamson et al. 1992). Hence, a general expectation we explore empirically is that some individual frames will be correlated, with some occurring in conjunction with others to form more complex frames. At this stage, without having conducted the analysis that will reveal which frames exist, we obviously cannot specify which frames will be correlated with which other frames. But we expect that at least some frames will occur together, and that their co-occurrence may be related to adoptions in other states. We state this expectation in general terms:

Hypothesis 4 (Frame Correlations): Individual frames will be correlated with each other, combining to form more complex frames, and prior adoptions will predict these correlations.

Methodology

Case Selection

Our analysis of policy frames as a part of the diffusion process concentrates on the adoption of anti-smoking policies in U.S. states. U.S. states historically have had considerable autonomy in the area of public health, and smoking restrictions are no exception. Although smoking-related

[5] See https://news.gallup.com/poll/237767/one-four-americans-support-total-smoking-ban.aspx.

[6] To some extent, this reasoning might also hold for another aspect: health. As argued earlier, beliefs regarding the health consequences of smoking, and of smoking bans, emerged in a prior period through a growing scientific consensus. These beliefs are strong and widespread, with polls since the 1970s revealing that more than 90% of Americans view smoking as having harmful effects on health (https://news.gallup.com/poll/3553/nine-ten-americans-view-smoking-harmful.aspx). At the same time, as discussed earlier, lawmakers might learn about health consequences that follow from adoptions. Overall, we remain agnostic regarding the status of the health frame, and refrain from associating it unambiguously with either the learning or emulation mechanism.

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 United States; rather, the vast majority of policymaking has taken place in the states. Thus, the issue of anti-smoking laws at the state level provides an excellent forum for examining diffusion and issue definition.

Our choice of policy area is also motivated by other considerations. First, several studies (Pacheco 2012; Shipan and Volden 2006, 2008; Studlar 1999), along with abundant anecdotal evidence, indicate that anti-smoking adoptions have exhibited a diffusion process. This allows us to concentrate on the nature of the process—in particular, the ways in which this issue has been defined—rather than the mere existence of the diffusion of adoptions. Second, smoking bans have been adopted in a convenient time frame—roughly a 15-year period—that is long enough to detect variation and to supply sufficient information, but short enough to be practically manageable. Third, there was significant uncertainty about the potential consequences of the policies along several dimensions, including economic consequences, popular support, interest group support and implementation concerns (Jacobson, Wasserman, and Anderson 1997). Finally, this uncertainty over consequences means that the debate over adoption can be framed in multiple ways. Although our case is specific, our results offer an excellent basis for research in other areas. We elaborate on this point in the conclusion.

Corpus

We discuss the construction of the corpus in detail in Appendix A in the supporting information (SI). Briefly, we retrieved and processed articles published in 49 newspapers covering 49 U.S. states between 1996 (two years before California adopted the first statewide smoking ban) and 2013.[7] We retrieved newspaper texts using a simple, broad keyword search from different database providers. To remove irrelevant paragraphs, we conducted a supervised text classification based on crowd annotation (Benoit et al. 2016) and a machine-learning classifier. The final corpus consists of 52,675 paragraphs.

[7] One question that arises is whether the media coverage we examine reflects how policies are framed or whether it influences the frames. On this question we are agnostic. Regardless of whether this coverage reflects or influences frames, media coverage can be used as an accurate source for identifying the ways in which smoking bans are framed and, more generally, as an indicator of how they are discussed (Baumgartner, De Boef, and Boydstun 2008).

Structural Topic Model

We identify policy frames inductively with a structural topic model (STM) (Roberts et al. 2014; Roberts, Stewart, and Airoldi 2016). Unlike other types of topic models (Blei, Ng, and Jordan 2003), the STM allows the inclusion of covariates. This makes it possible to assess relationships among variables in a regression-like framework, that is, to uncover covariation between topic prevalence and variables of interest. Concretely, in our study, the STM's ability to include covariates means that we can directly examine our expectation that topic prevalence within a state—which is our measure of issue definition—is linked to prior policy adoptions by other states. Moreover, the STM allows us to control for other factors that might be related to topic prevalence, including time trends.[8]

We estimate our topic models using the stm package in R (Roberts, Stewart, and Tingley 2014). We evaluated 48 models, varying the number of topics from 3 to 50, and found that models with relatively few topics performed better (see SI Appendix C.1). After a qualitative evaluation of the most-probable words and documents of the models' topics in this range, we selected the 12-topic model as the most useful for our analysis. The results of models assuming three to 13 topics show that the models identify the same underlying topics, although obviously with different degrees of granularity.

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

Covariates

The most important covariate in our analysis measures *prior policy adoptions by other relevant states*. The construction of this variable mirrors that of a spatial lag,

[8] We discuss the covariates that we include in our analysis in the next section.

which is a weighted average of the policies of other states (Plümper and Neumayer 2016) and is the key variable of interest in most diffusion studies. To construct this spatial lag, we first 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 bans in seven areas: restaurants, bars, government worksites, private worksites, hotels, malls, and indoor arenas (see SI Appendix B).

As noted earlier, not all states may matter equally in terms of the relationship between prior adoptions and issue definitions. There are a variety of ways that we could create a connectivity matrix containing information about which states are likely to influence other states. For example, the literature on diffusion traditionally has relied on geographic proximity (Maggetti and Gilardi 2016). This approach, however, limits the focus of the analysis to a narrow set of states—namely, those sharing a border with the state in question. At the other extreme, we could include all other states in our connectivity matrix.

The approach that we use relies on a recent innovation by Desmarais, Harden, and Boehmke (2015), which identifies a latent, dynamic policy diffusion network for U.S. states. That is, for any given state, it identifies the other states that have shown influence on the state in question across a large range of policy areas. 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 adoptions; and the accuracy with which a policy adoption by *i* predicts an adoption by *j*. Applying a latent network inference algorithm to the adoption of 187 policies, these authors infer a state-to-state policy diffusion network for 1960 through 2009. That is, for each pair of states, they estimate whether policies diffuse from one state to the other, and in which direction. The result is a directed dyadic data set that can be used to construct a binary connectivity matrix, similar to a traditional geographic contiguity matrix, but reflecting the latent diffusion network more accurately than geography.[9] Our approach thus allows for a broader set of potentially relevant states than would an approach using only geographic neighbors, but a more focused set than one that includes all other states. We hasten to add, however, that we have run our analysis using all of these approaches—the latent diffusion network, neighboring states, and all states—and find similar support for our expectations across these different operationalizations (see SI Appendix C.2).

The analysis includes several other covariates that we use to control for relevant factors that might affect how smoking bans are framed: (1) a monthly trend variable, to control for the baseline time trend of topics' proportions; (2) newspaper IDs, to identify the states in which newspapers are based; (3) newspapers' ideological "slant" (Gentzkow and Shapiro 2010), since a newspaper's ideological leaning might affect its coverage of smoking bans; (4) the percentage of smokers in the state where the newspaper is based, which might be related to the popularity of smoking bans; (5) whether a newspaper is based in a tobacco-producing state (for the same reason); (6) whether Democrats or Republicans form a unified government in a state, because the two parties tend to have different views about smoking restrictions; (7) the presence of smoking bans in a state; (8) the number of months before and after the enactment of smoking bans, since the framing of smoking bans is likely to change before and after their introduction; and (9) the sentiment of a given paragraph, which we measured with the same approach we used for the identification of relevant paragraphs (see SI Appendixes A.3 and A.4).

Results

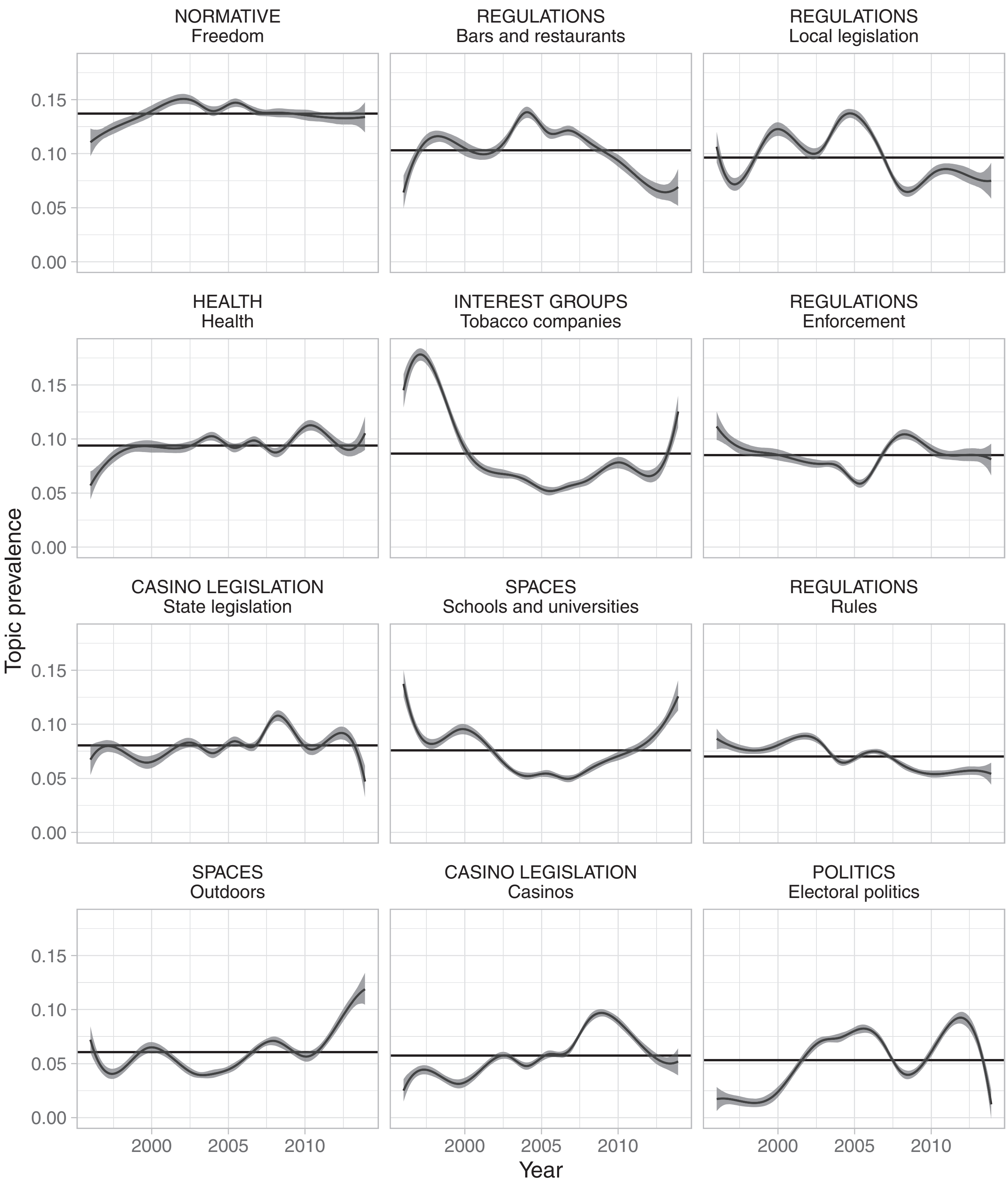
Topics and Time Trends

Figure 1 shows how topic prevalence is distributed over time across all states; a detailed validation is discussed in SI Appendix C.3. We determined the label for each topic based on the top 50 words for each topic (see SI Appendix C.4), as well as a reading of the most relevant paragraphs for each topic (see SI Appendix C.6). The model does an excellent job of identifying relevant topics that are clearly connected with smoking bans and are consistent with what public-health experts found by hand-coding documents (e.g., Menashe and Siegel 1998).

We group the 12 topics into seven categories, based on both how they correlate with one another (as discussed earlier) and our theoretical arguments. The "Normative" category consists of *Freedom*. Figure 1 shows that *Freedom* is on average the most prevalent topic, with little change over time after 2007. "Health," the second category and fourth most prevalent topic, also is relatively stable over time compared to other topics. Empirically, the *Freedom*

[9] Desmarais, Harden, and Boehmke (2015) show that diffusion occurs most commonly across states that are *not* contiguous. Since their diffusion network data are available only until 2009, we predicted the remaining years (2010–13) using temporal exponential-family random graph models, whose forecasts were trained and evaluated with data for the 14 years available in their article. See SI Appendix D.

FIGURE 1 Topic Prevalence over Time



Note: Topics are sorted by decreasing average prevalence. Horizontal lines show average prevalence for each topic over the observation period. Topic labels are in sentence case, whereas categories are in upper case.

and *Health* topics clearly co-occur, as we will show in the next section. However, for the reasons discussed in the section "Theoretical Expectations," we do not group them in the same category.

The "Regulations" category includes *Bars and Restaurants*, *Local Legislation*, *Rules*, and *Enforcement*.[10] These topics are among the most frequent, and some exhibit marked variation over time. "Interest Groups" and "Politics" consist of one topic each (*Tobacco Companies* and *Electoral Politics*, respectively). *Tobacco Companies* is on average relatively prevalent, but peaked before 2000. *Electoral Politics* is the least frequent topic, with some ups and downs. Finally, "Casino Legislation" includes both *Casinos* and *State Legislation*, and "Spaces" includes *Schools and Universities* and *Outdoors*.

These time trends offer important context for interpreting our main results. Importantly, the time trends are controlled for when examining other variables of interest, including in particular the share of prior policy adoptions by other relevant states

Assessing Our Expectations

Diffusion. We begin with our first expectation, which is that issue definitions within a state are predicted by other states' prior adoptions of smoking bans. We can assess this expectation by plotting the prevalence of a frame against the proportion of prior adoptions by those other states, to see whether the prevalence covaries with earlier adoptions or is unrelated to these adoptions. Again, we find similar results using neighboring states and all states (see SI Appendix C.2).

Figure 2 provides direct evidence that the prevalence of some topics is indeed predicted by prior policy adoptions by other states. *Rules*, *Bars and Restaurants*, *Local Legislation*, and *Tobacco Companies* all show a pattern of decreasing prevalence as the proportion of adoptions increases. Meanwhile, *Enforcement*, *Casinos*, *Electoral Politics*, *Outdoors*, and to some extent *State Legislation* show the opposite effect, with these frames becoming more prevalent as more states adopt bans. Not all topics, however, vary in prevalence relative to the share of prior adoptions. In particular, *Health* and *Freedom* show no covariation with prior adoptions, a finding we return to shortly.

The plots thus provide evidence consistent with our first expectation about diffusion, showing that many, although not all, topics are predicted by levels of prior adoptions. We now turn to our second and third expectations, both of which are based on the mechanisms of diffusion.

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

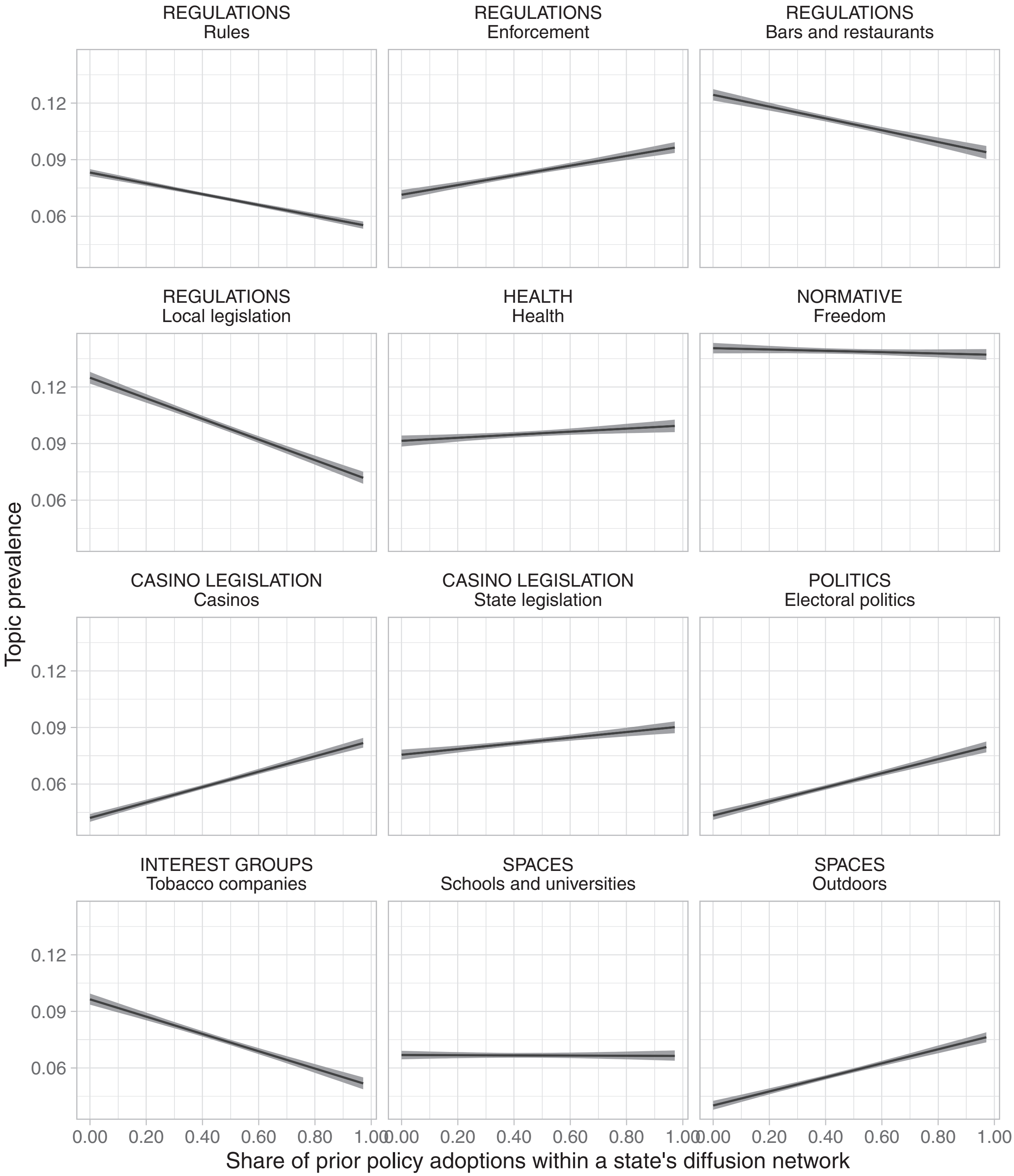
Several of the plots in Figure 2 provide support for these conjectures. We begin by considering topics within the "Regulations" category, which includes topics related to concrete aspects of smoking bans. We find that the correlation between prevalence and prior adoptions is strong—and negative—for *Bars and Restaurants*, indicating that the prevalence of this topic decreases as a higher proportion of other relevant states adopt anti-smoking laws. Opponents of smoking restrictions regularly voiced concerns about the potential harmful economic effects of such policies on bars and restaurants. The texts in SI Appendix C.6 (p. 25) illustrate how patrons were initially ambivalent (e.g., "Galen Sprague and Marchello Marchese say they don't mind stepping outside to take a cigarette break"; "'I like to sit down for a while and smoke before I eat', said Lawson. 'And after I eat I like to smoke'."). The predictions of harm were not borne out, however (Warner 2000). Consequently, this frame faded.

A negative correlation also occurs for the *Rules* topic within this category. As illustrated by the texts shown in SI Appendix C.6 (pp. 20–21), this topic identifies the technical aspects of smoking bans, such as rules or permits for separate smoking areas, ventilation, and exemptions (e.g., "An 'effectively smoke-free' establishment limits smoking to separately ventilated areas"). Getting these regulations right is important, as uncertainty surrounding them may worry business owners. Figure 2 shows a negative correlation between *Rules* and prior adoptions by other relevant states, indicating that these issues are quite salient when no other state within the diffusion network has enacted smoking bans, and less so when many have. This finding suggests that the experiences of other states are used to update beliefs—in this case, what kind of regulations work best or the challenges regarding their design.

Enforcement is another practical aspect of smoking bans in the same category. The salience of this topic increases as more evidence from other relevant states becomes available, showing that the enforcement of smoking bans is not always unproblematic. For instance, the examples in SI Appendix C.6 (p. 24) show that some business owners filed lawsuits challenging the scope and legality of smoking bans (e.g., "Bar owner's smoking ban suit dismissed"). The last correlation in this category, that

[10] We discuss the distinction between *Rules* and *Enforcement* in depth in SI Appendix E (p. 27).

FIGURE 2 Topic Prevalence and the Share of Prior Adoptions within a State's Diffusion Network



Note: Topic labels are in sentence case, whereas categories are in upper case.

for *Local Legislation*, is also negative (e.g., "Naperville officials this week delayed voting on a proposed smoking ban"). This finding suggests that the decision-making process may shift from the local to the state level when state legislation becomes more widespread. Interestingly, *Health* is essentially unrelated to the share of prior policy adoptions by other relevant states.

We find evidence for our learning expectation in other categories. Consider the "Casinos" category, which includes legislation introducing smoking restrictions in casinos. The specific *Casinos* topic within this category becomes more salient when many states enact smoking bans, suggesting that their experience points to negative consequences for the casino business, as illustrated by the examples in SI Appendix C.6 (e.g., "The industry has attributed the struggles largely to the sluggish economy and a smoking ban that went into effect in January 2008," p. 25). As more states adopt laws, and as evidence begins to amass about potential harmful consequences, learning occurs and the topic is more likely to emerge as a frame.

Next, our findings for topics in the "Politics" and "Interest Groups" categories indicate that states can learn not only from policy outcomes in other states; they also can learn about political outcomes. *Electoral Politics* identifies voters' involvement in the decision-making process, and more generally the political-electoral dimension of smoking ban adoption and implementation (e.g., "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"). It becomes a much more prominent topic when other states start to pass smoking restrictions.

Figure 2 also shows that another prominent political dimension, that of the dominant interest organization in this area—*Tobacco Companies*—is strongly and negatively correlated with the policies in other states. That is, as more states adopt these restrictions or bans, *Tobacco Companies* is less likely to emerge as a topic or frame. Given that restrictions and bans are usually adopted over the opposition of this industry, and given the growing public distrust of these companies during the period we examine, the increasing success of other states in adopting such policies means that states may no longer view tobacco companies as pivotal actors and consequently see less need to defer to them (e.g., "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").

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

To examine this expectation, we consider the "Normative" category. The topic in this group, *Freedom*, is not linked to concrete aspects of smoking bans that can be verified by looking at the experiences of other states. In particular, the compatibility of smoking bans with individual freedom can potentially become taken for granted and achieve a status in which they are, to again quote Finnemore and Sikkink (1998, 895), "no longer a matter of broad public debate." Therefore, we expect a negative correlation between normative topics and previous adoptions by other states.

Contrary to this expectation, Figure 2 shows that topics in the "Normative" group are not correlated with the policies of other states. In particular, *Freedom* is discussed with about the same frequency regardless of how many other states have enacted bans. The compatibility of smoking bans with individual rights (e.g., "Regardless of what ban supporters say, this is not about public health; it's about controlling the lives of others"; see SI Appendix C.6, p. 21) is highly salient in public debates on smoking bans—indeed, it is the most frequent topic (see Figure 1)—but its relevance does not increase or decrease, relative to other topics, when more states adopt the policy. That is, the experiences of other states do not change the frequency—again, relative to other topics—with which smoking bans are discussed in connection with individual rights, implying that although *Freedom* is an important part of the debate, it is not a crucial dimension of the *diffusion* of smoking bans.[11]

Topic Correlations. We now turn to our expectation about the connections among individual topics. In examining correlations between topics, we consider both their nature and how they covary with the share of prior policy adoptions in other states. Figure 3 shows, in network format, how our individual topics correlate with one another. For the reasons explained earlier, we concentrate on positive correlations. The top panel of Figure 3 shows correlations computed using the whole corpus and is the basis for the categories we have used so far. The middle

[11] Although we did not assign *Health* to the "Normative" category, this frame also shows little change corresponding to the number of earlier adoptions (and unlike *Freedom*, it increases very slightly). The examples in SI Appendix C.6 (p. 20) show texts relevant to *Health* that mention scientific studies, including those conducted in other countries, and refer to their findings as "facts," supporting the idea that the scientific consensus has gained broad acceptance.

FIGURE 3 Topic Correlations

Note: Topic correlations over all paragraphs (top panel) and as a function of low (center panel) or high values (bottom panel) of the share of prior policy adoptions within a state's diffusion network.

panel computes correlations using the subset of texts for which the values of the spatial lag is smaller than or equal to 0.5—that is, cases in which less than 50% of other states have adopted the policy. Finally, the bottom panel shows the correlations when most other states have adopted the policy.

The main pattern that emerges from Figure 3 is that topics tend to be more closely linked with one another when more states adopt the policy. In other words, policy frames tend to become more complex as the policy diffuses. When few other states have adopted the policy (i.e., the middle panel), *Rules* and *Enforcement* tend to be discussed together, but not in conjunction with other topics. The same holds for *Health* and *Freedom*, suggesting again that *Health* might share some features with the normative category of *Freedom*. Moreover, several topics are discussed in isolation.

However, when many states have adopted the policy, we see the emergence of a broad frame connecting many topics. The central node of this frame is *Rules*, with connections not only with *Enforcement*, but also with *Health* and *Freedom* (via *Bars and Restaurants*) and *Electoral Politics* (via *Local Legislation*). That is, a much more complex frame emerges, combining practical, normative, and political aspects. This evidence suggests that policy diffusion is associated with policy frames taking more sides of the problem into account. Moreover, additional analysis in SI Appendix C.5 (p. 19) shows that the emergence of more complex frames goes together with a smaller number of distinct topics, suggesting that the more complex frame crowds out other frames.

Summary

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

Conclusion

Our study brings a new perspective to the study of policy diffusion by focusing on framing and issue definition. Rather than examining whether policy adoptions are a function of previous adoptions, which has been the standard approach, we instead investigate another aspect of diffusion, one that has been overlooked and for which no conventional wisdom exists. Namely, we have examined the link between prior adoptions and the way an issue is defined or framed.

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

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

We also show that there is another benefit to focusing on stages prior to adoption. Explaining whether a policy is adopted, which has been the standard approach in diffusion studies, is certainly valuable. But for this approach to work, the policy under study must be widespread; otherwise, the data set will include too many 0s and too few 1s in the dependent variable for the analysis to be reliable or even feasible. Moreover, policies must be easily measurable and comparable. However, many important policies cannot be easily measured or compared across units; and many phenomena may not (yet) be widespread. In such cases, a conventional diffusion approach that focuses on adoptions as a dependent variable is not useful, even though a diffusion *perspective*—one showing how policymaking activities in previous and current states are related—might be highly relevant. Our approach shows how scholars can study any policy or a range of political phenomena from a diffusion angle, regardless of whether policies have been adopted. Thus, it can shed light on policy areas that, unlike anti-smoking laws, do not include frequent adoptions. In such areas, our findings lead us to expect that there will be a larger number of unconnected frames. Moreover, we expect that normative frames will already be prominent and remain so throughout the diffusion process.

Our study sets the stage for the examination of an additional set of theoretical and empirical questions. Notably, many of these questions would not have been apparent before our analysis. For example, some studies have established that the diffusion of innovations is conditional on the strength of interest groups and the capacity of the legislature. Do such political variables condition the diffusion from adoptions to the issue-definition stage?

In addition, we have examined diffusion and the issue-definition stage within one particular policy area. As we have explained, smoking restrictions presents an especially good area in which to examine this topic, given the existence of multiple frames, the relatively short period in which policies were considered, and so on. Thus, we are confident that our approach and results provide a good template for how to examine other policy areas that meet these criteria, including changes to the death penalty, abortion, gun safety, same-sex marriage, and marijuana liberalization. At the same time, it will certainly be worthwhile to explore whether similar patterns exist in other policy areas. In particular, for our analysis, we relied on the use of latent diffusion networks (although we emphasized that our results are robust to examining other sets of relevant states). The latent network we used was based on all policies, but it can be used to determine networks based on subsets of policies. This would allow scholars to examine a network that was created based only on related policies or policies that include certain sorts of frames, such as freedom.

Another question that our analysis allows scholars to consider concerns the direct link between policy frames in earlier states and those 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. Consequently, although we can include prior adoptions as covariates, we cannot include the prevalence of earlier frames in other states as a covariate in the STM because this prevalence is unknown prior to estimating the model. A study that builds on our article and examines the link between frames in different states would be an illuminating addition to the diffusion literature. Similarly, future studies should work to develop new ways to assess the link between sentiment and framing as a measure of issue definition. Combining topics and sentiment in a coherent outcome variable is difficult within our methodological approach because although we included sentiment as a covariate, measured prior to the analysis, topics are identified inductively together with their correlation with covariates.

Studies building on our approach also should aim to develop ways to strengthen the connection between theoretical expectations and empirical analysis to better cope with its inductive aspects. One challenge to overcome is the formulation of specific hypotheses when topics are unknown because they are yet to be identified by the model. Finally, future research should attempt to go beyond prediction to measure causal effects. It is a daunting task in this context because it requires solving simultaneously two difficult problems that the literature is just starting to address individually (but not yet in conjunction): causal inference with text data (Egami et al. 2018) and the identification of causal diffusion effects using observational data (Egami 2018).

While acknowledging the relevance of these other questions and topics, it is worth repeating that they arise in large part because of the work presented in this article. Until now, there has been no investigation of the connection between prior adoptions and the beginning steps of the policy process (i.e., issue definition and policy frames) in later states. The primary value of our approach is that it provides a new, innovative way to investigate this connection. On its own, this constitutes a valuable addition to the literatures on policymaking and policy diffusion. But it also provides a foundation that other studies can build on to explore new avenues that will further enrich our understanding of diffusion and the policy process.

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Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix A: Corpus
Appendix B: Discussion of distinct smoking restrictions
Appendix C: Topic models
Appendix D: Extrapolation of diffusion networks
Appendix E: Distinction between "Rules" and "Enforcement" topics