The Diffusion of Policy Perceptions: Evidence from a Structural Topic Model*

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Abstract

Policy diffusion occurs when policies in one unit (e.g., states, cantons, cities) are influenced by the prior adoption of policies in other units. Although numerous studies have convincingly shown that policy adoption is a function of previous adoptions in other units, they have, with very few exceptions, generally ignored a crucial step in the diffusion process—namely, how political units perceive the policies that they are considering adopting. This *policy perception* plays a crucial role in linking the actions of previous units with the potential actions in other units. In this paper we focus on the link between prior adoptions and policy perceptions, both by identifying the mix of perceptions and by examining the link between prior adoptions and policy perceptions. We study these perceptions in the area of restrictions on smoking in U.S. states. Our analysis draws upon an original dataset of about half a million articles published in thirty-eight American newspapers between 1996 and 2014 and uses structural topic models to estimate how smoking bans have been perceived and how perceptions change as a function of policy adoption in other states. We find that many of the most prominent topics are indeed a function of prior policy adoptions in other states.

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1 Introduction

When political units—states, cities, or even countries—adopt policies, they do not do so in a vacuum, basing their decisions on only internal factors and pressures. Instead, they can observe the actions that other units previously have taken with respect to these policies. Thus, a state that is deciding whether to adopt, say, new gun control laws, or new rules concerning eligibility for various state-funded medical services, can look around to see which other states have adopted such policies, as well as what types of policies these other states have adopted. They can then base their own decisions on what they observe in these other units.

This process, known as *policy diffusion*, has been the focus of a large and rapidly growing number of studies (Dobbin, Simmons and Garrett, 2007; Gilardi, 2012; Graham, Shipan and Volden, 2013; Maggetti and Gilardi, 2016). These studies have convincingly established, across a wide range of policy areas, that policies do indeed diffuse, with policies in one unit influenced by policies in other units. That is, these studies have demonstrated that when a unit is considering what to do about a policy, the likelihood that it will adopt the policy is influenced by the existence, in other units, of similar policies.

Although the link between new policy adoptions and earlier policy adoptions has been well established, the focus of the vast majority of studies of policy diffusion has been exclusively on the final adoption decision—that is, did the unit adopt the policy, or did it fail to do so? Although this focus is understandable and has produced numerous important insights, it also ignores a key earlier stage in the policymaking process. In particular, the adoption decision arrives only after the unit has considered various aspects of the policy. During this stage, the unit forms *policy perceptions*. These perceptions can shape the final outcomes, including whether to adopt a policy and what form the policy should take. But these perceptions, as part of the diffusion process, can themselves be shaped by the prior policy adoptions that have taken place elsewhere. Thus, a more complete consideration of the interdependence of policymaking needs to account for the link between earlier adoptions and the way that a unit perceives how policy problems and solutions are defined and understood.

To examine how the perception of policy problems and solutions changes as a function of the adoption of policies elsewhere, we focus on anti-smoking laws—policies restricting or banning smoking in public places—in the United States. Our choice of policy area is motivated by several considerations. First, several American studies (e.g., Shipan and Volden, 2006, 2008, 2014; 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 instead of its mere existence. Second, smoking bans have been adopted in a convenient time frame—roughly a ten year period—which 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—economic consequences, popular support, interest group support, ease of implementation, and so on. And finally, this uncertainty over consequences means that the debate over adoption can be perceived in multiple ways.

In our empirical analysis we rely on an original dataset of almost half a million articles published in thirty American newspapers between 1996 and 2014. More specifically, we use structural topic models (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016) to identify how these articles have discussed anti-smoking laws and to estimate how these laws have been perceived in the states. We then show how these perceptions change as a function of policy adoption in nearby states.

2 Stages of the Diffusion Process

Policy diffusion occurs if the policy choices of one unit (e.g., countries, states, cities, etc.) are influenced by the policy choices of other units (Dobbin, Simmons and Garrett, 2007; Gilardi, 2012). Although this simple definition captures key elements of the diffusion process, it also omits others. Consider a situation in which State A is deciding whether to adopt a new law. The standard approach, found in most analyses of policy diffusion, is to consider whether State B already has adopted this policy; and then to see whether State B's adoption affects the likelihood that State A adopts the policy.[1] In effect, then, these studies implicitly model diffusion as a two stage process; what happens in between these two stages is rarely seen as important.

We argue instead that the process of diffusion occurs in three stages, not two. First, State B adopts a policy. Second, State A then forms perceptions of this policy. And third, State A then decides whether to adopt the policy.[2] The middle stage, in which State A forms its policy perceptions, is more than just a transitional stage; it is worthy of attention in its own right. It is at this stage, when states are

[1] Although we refer to "State B," the earlier adoption can be by a single state, as in analyses that examine dyadic relationships between individual states, or by a set of states, as in studies that look at the number of previous adoptions among a specified set of states.

[2] It is also possible to consider an earlier stage—namely, the way in which the policy is framed prior to State B's adoption. Although this is certainly a topic worthy of attention, we leave it for future research.

considering what to do and forming perceptions of a policy, that they might consider some of the factors that scholars refer to as the mechanisms of diffusion (Simmons, Dobbin and Garrett, 2006; Braun and Gilardi, 2006; Dobbin, Simmons and Garrett, 2007; Gilardi, 2012). What can they learn about the political or policy consequences of adoptions in earlier states? Would they be likely to suffer negative economic consequences, or would the reap positive economic benefits, if they adopt such a law? Are there norms in place to which they want to adhere, or would they be acting against prevailing norms by adopting a new policy?

More generally, there are clear links between this second stage, in which a state forms policy perceptions, and the first and third stages. Our focus in this paper is on developing a way to characterize the policy perceptions that exist at the second stage, and to investigate whether there is a connection between the adoptions in the first stage and the perceptions in the second stage. But it is worth noting that this connection is important in part because of the link between the second and third stages. This link between the latter two stages is both straightforward and of obvious importance. Put simply, does the way in which an issue is perceived within a polity have an effect on the likelihood that the polity will adopt a policy? Especially given that policies usually can be framed in multiple ways, does the specific frame that dominates discussion influence the eventual policy choices? Viewed in this light, policy perceptions are important as a *cause* of policy outcomes.

Our main interest in this paper is instead on the relationship between the first and second stages, which means that we examine policy perceptions as an *effect*. Given that State A's consideration of an issue is subsequent to State B's action, we investigate whether State B's action influences the policy perceptions in State A. In the area of anti-smoking laws, for example, one state might perceive the policy as being primarily about the health consequences of adoptions restrictions on smoking, while another might concentrate on public support. Does the type of perception change over time? And is this perception in a state influenced by the actions taken earlier in other states? In effect, then, our focus is on whether the diffusion process involves policy perceptions, whereby these perceptions—which might eventually influence further outcomes—are themselves a product of diffusion from the actions of other actors. Thus, instead of focusing on the direct diffusion from one set of policy outcomes to another, our interest in this paper is in establishing whether previous policy outcomes diffuse to policy perceptions—a key aspect of the diffusion process that few studies have recognized, let alone examined.[3]

[3] A notable exception is Pacheco's (2012) study, which not only examines how prior adoptions influence public opinion,

To assess which policy perceptions exist and are most prevalent, and whether the prevalence of these perceptions is a function of prior adoptions (and thus part of the overall diffusion process), we rely on structural topic models (STMs) (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016), which we describe in more detail in the following section. This approach allows us to examine, in great detail, which topics dominate the discussion surrounding a policy. We identify and measure the topics by analyzing media coverage of this policy issue.

One question that arises is whether the media coverage we examine reflects how policies are perceived, or whether it influences this perception. On this question we are agnostic. Regardless of whether this coverage reflects or influences perceptions, it can be used as an accurate source for identifying the ways in which smoking bans are perceived in a given unit. Thus, we can use the information derived from structural topic models both to identify the most common perceptions and to identify their distributions, both cross-sectionally and over time. In the analysis in this paper, we will look specifically at whether the prevalence of specific topics is a function of adoptions in other states—that is, whether policy perceptions change as a function of the adoption of smoking bans in other units. But our data could be used to examine several other aspects of policy perceptions, such as whether the mix of these perceptions (e.g., the ratio of different perceptions or another composite measure) varies over time, whether the topics used focus less on economic consequences over time, and whether states exhibit the same topics that are found in similar states.

3 Methodology

3.1 Data sources and preprocessing

Our analysis of policy perceptions as a part of the diffusion process concentrates, as noted earlier, on the adoption of antismoking policies in the U.S. states. The states traditionally have had considerable autonomy in public health areas, and smoking restrictions are no exception. Although smoking-related issues are often discussed 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 topic of anti-smoking laws provides an excellent forum for examining the process of diffusion.

The time frame we examine begins in 1996, which is two years before the first statewide smoking

but also investigates whether these changes in public opinion then influence adoptions.

ban was adopted in California.[4] To analyze public discussions and to gain a handle on policy perceptions within a state, we rely on articles published in the newspapers listed in Table 1. Currently we have processed articles from thirty-eight newspapers, but the full construction of the newspaper corpus is still under way and the final corpus eventually will include the largest newspaper in terms of circulation for every state. 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).

We retrieved newspaper texts using a simple, broad keyword search[5] from different databases such as LexisNexis. Then we split the texts into paragraphs of a similar length,[6] which produced a corpus containing 3,519,683 paragraphs. A manual evaluation of a random sample of 15,519 paragraphs[7] revealed a very low share of paragraphs actually covering smoking bans—about 1.5% on average. This is due to the looseness of our keyword search, aimed at minimizing the number of articles of smoking bans escaping our search. We manually annotated this sample of paragraphs as relevant or irrelevant. 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 coded as irrelevant paragraphs discussing, for example, smoking bans introduced by private actors (e.g., companies, businesses), or bans of specific tobacco products (e.g., mentholated cigarettes).

Using the information gained by manual coding, we then classified all 3,519,683 paragraphs in our corpus as relevant or irrelevant using a two-step support vector machine (SVM) classification, implemented in the Python module `scikit-learn`. Prior to the estimation we pre-processed all documents with standard procedures such as text segmentation into paragraphs and sentences, tokenizing, re-

[4]Debates on smoking bans go back at least to the introduction of the first smoke-free spaces in the 1980s. The Minnesota Clean Indoor Air Act, for example, called for a partial smoking ban in bars and restaurants as early as 1975. However, the analysis requires significant public debates associated with highly visible events.

[5]The keyword string for the different newspaper database was an adaptation of "tobacco OR non-smoking OR anti-smoking OR smoking OR cigar! OR (lung AND cancer) OR smoker," depending on the options available for Boolean operators and truncation wildcards.

[6]The original paragraph structure of the documents was kept, but paragraphs with fewer than 150 tokens were collapsed until the collapsed paragraph exceeded 150 tokens. This ensures the basic comparability of the texts from different newspapers.

[7]Usually, a much smaller sample of hand-coded documents is necessary (Grimmer and Stewart, 2013). In our case, however, the search string matched a lot of documents that covered smoking in other contexts (e.g., smoking in movies, health problems unrelated to regulation, restaurant reviews mentioning that a restaurant is non-smoking, etc.). Consequently, we had to increase the sample for the manual annotation in order to produce enough relevant paragraphs for the supervised classification.

Newspaper	State	N articles	N paragraphs	N filtered
Albuquerque Journal	NM	4,953	25,464	1,273
Argus Leader	SD	3,801	25,339	1,235
Arizona Republic	AZ	9,405	44,455	2,360
Atlanta Journal	GA	23,281	114,843	2,443
Baltimore Sun	MD	14,096	78,124	2,061
Boston Globe	MA	19,337	112,465	3,407
Burlington Free Press	VT	1,938	10,607	407
Charleston Gazette	SC	18,228	116,099	2,284
Chicago Tribune	IL	31,855	157,102	4,986
Clarion Ledger	MS	3,206	17,005	502
Courier Journal	KY	10,593	71,887	3,041
Daily News	NY	14,202	60,828	1,406
Daily Oklahomean	OK	12,250	44,793	1,214
Denver Post	CO	13,088	79,843	1,773
Deseret News	UT	15,884	58,817	1,230
Des Moines Register	IA	5,750	41,160	1,142
Detroit Free Press	MI	11,309	115,380	1,195
Hartford Courant	CT	14,821	83,980	1,215
Honolulu Advertiser	HI	1,465	8,282	227
Las Vegas Review Journal	NV	9,430	56,605	1,178
Los Angeles Times	CA	29,597	196,061	3,255
Milwaukee Journal Sentinel	WI	16,040	81,146	1,332
New Jersey Record	NJ	19,453	95,395	1,977
New York Times	NY	53,411	344,898	5,315
News Journal	DE	5,426	31,177	1,513
Omaha World Herald	NE	12,295	72,506	2,420
Philadelphia Inquirer	PA	18,975	105,861	2,418
Portland Press Herald	ME	5,374	27,796	787
Providence Journal	RI	15,264	89,549	2,032
Star Tribune Minneapolis	MN	13,693	120,220	2,545
St. Louis Post Dispatch	MO	27,516	137,830	3,777
Seattle Times	WA	22,971	139,448	1,347
Tennessean	TN	5,475	36,611	740
Tribune Eagle	WY	2,024	13,526	848
Union Leader	NH	975	3,944	69
USA Today	NY	11,246	59,637	900
Wall Street Journal	NY	22,971	139,448	1,413
Washington Post	DC	58,495	501,552	5,486
Total		580,093	3,519,683	72,753

Table 1: *Selected sources for the content analysis.*

moval of punctuation, collapsing of n-word geographical names such as "New York" to one token ("New_York"), as well as lemmatizing, part-of-speech tagging and converting all words to lowercase (Hopkins and King, 2010). The SVM has proven to be the most effective classifier for our task, outperforming a kernel ridge regression and a multinominal naïve bayes classifier as well as an ensemble of all three classifiers. We proceeded in two steps. First, we applied an SVM classifier optimized for recall[8] (0.90 recall for the relevant paragraphs in the heldout set). Second, we re-trained another SMV classifier, now giving recall and precision[9] equal weight in the training round (0.74 recall and 0.72 precision for the relevant paragraphs in the heldout set). Hence, the filter is able to keep 67% of the relevant paragraphs (0.90×0.74), while it removes about 95% of the irrelevant paragraphs. In the end, the filter produced a corpus of 72,753 paragraphs containing 103,647 unique terms and 5,278,999 instances of these terms. Moreover, most classification runs we tested agreed with an overall F-Score of 0.80 or higher—a further sign for the consistency and thus reliability of the classification (Collingwood and Wilkerson, 2012). Therefore, we are confident that our estimations reveal the general trend in the newspapers' coverage of smoking bans.

3.2 Estimation

We identify policy perceptions inductively with a structural topic model (STM) (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016), which produces estimates document-topic and word-topic probabilities (Roberts, Stewart and Airoldi, 2016; Roberts, Stewart and Tingley, 2014). It builds on well-established generative topic models, such as the Latent Dirichlet Allocation (LDA) (Blei, Ng and Jordan, 2003). The LDA is a mixed-membership model, meaning that it assumes that each document consists of a mixture of topics (Grimmer and Stewart, 2013, 283–285). Concretely, the LDA is a hierarchical model in which a document's i proportion of topics has a common prior drawn from a Dirichlet distribution:

$$\pi_i \sim \text{Dirichlet}(\alpha).$$

Then, the topic of the j-th word in the i-th document is drawn from a multinomial distribution:

$$\tau_{ij} \sim \text{Multinomial}(\pi_i).$$

[8]Recall is the fraction of relevant documents that are retrieved.

[9]Precision is the fraction of retrieved documents that are relevant.

Finally, the j-th word in the i-th document is drawn from a multinomial distribution, conditional on its probability of being drawn from topic k, θ_k:

$$w_{ij} \sim \text{Multinomial}(\theta_k).$$

The STM's major innovation is that the prior distribution of topics can be influenced by covariates (Roberts et al., 2014; Roberts, Stewart and Airoldi, 2016):

$$\pi_i \sim \text{LogisticNormal}(X\beta, \Sigma).$$

Furthermore, covariates can also be specified for the word distribution over topics, that is, not only the probability of topics within documents, but also that of words within topics. For instance, this would allow to see how the language used in a given topic changes as a function of covariates. We will consider this useful option in future work.

Our analysis includes a range of covariates: (1) month dummies, (2) newspaper IDs, (3) the "sentiment" of a paragraph, (4) the percentage of smokers in the state where the newspaper is based, (5) three political indicators (the share of democratic seats in the lower house and whether Democrats or Republicans form a unified government in a state), (6) the presence and month of enactment of smoking bans in a state, (7) the number of months before and after the enactment of smoking bans, and (8) the presence of smoking bans in other states ("spatial lag"). Variables 6–8 consider smoking bans in seven areas: restaurants, bars, government worksites, private worksites, hotels, malls, indoor arenas. That is, we computed variables 6–8 separately for smoking bans in each of these areas, and include them all in the models.

For the sentiment analysis, we use an adapted implementation of `word2vec` (Mikolov and Dean, 2013), which learns and aggregates term similarities through a shallow neural network process. The implementation we use is adapted to documents (`doc2vec`), which allows to consider paragraph and sentence structures as well (Qiu, 2015). We build a `doc2vec` model using our smoking ban paragraphs and 50,000 IMDB movie reviews labelled as positive or negative (Maas et al., 2011). Tested on another 12,500 movie reviews, we achieve an accuracy of 84% for a binary classification into positive and negative. This analysis is in a very early stage. In further iterations, we will obviously have to conduct evaluations on the smoking ban paragraphs directly and, more generally, improve our strategy to measure sentiment.

The spatial lag is the most interesting variable, both substantively and theoretically, and we use it to estimate diffusion effects. In this context, a spatial lag is simply a weighted average of the policies of other states. To construct a spatial lag, we need two pieces of information. First, we need to know when various types of smoking bans were enacted and implemented in all the states. We purchased these data from MayaTech's Center for Health Policy and Legislative Analysis, which has already proven to be a highly reliable data source (Shipan and Volden, 2006). Second, we need a connectivity matrix containing information on the relationship between states, specifically, which 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 tends to perform well in practice despite its theoretical bluntness. Several alternatives have been put forward, most of which are tailored to specific policies. A valuable general indicator has recently been put forward by Desmarais, Harden and Boehmke (2015), based on the adoption patterns of many policies over a long period of time (but only until 2009). We estimated models using both geographic proximity and the new Desmarais, Harden and Boehmke (2015) measure, but we report only the former.

We estimate two models: A first model runs on the full newspaper corpus. A second model uses the spatial lag based on the influential states identified by Desmarais, Harden and Boehmke (2015), which is only available for the time period from 1996 to 2009 and for all states except the District of Columbia.

A crucial decision in every application of a topic model pertains to the granularity, i.e. the number of topics. A topic model with too few topics will produce overly broad, diffuse topics, while a model with too many topics will results in many small, hardly distinguishable topics (O'Callaghan et al., 2015). An increasingly popular strategy to resolve this problem is to compare the coherence of different topic models. We again use `word2vec` to this purpose (Mikolov and Dean, 2013). By comparing the coherence within and between the vectors of most probable words for each topic model, `word2vec` suggests a granularity of 20 out of a candidate range of 3 to 23 topics for both of our models (see Figure A1).

4 Results

4.1 Media attention to smoking bans

Figure 1 shows the frequency of newspaper coverage of smoking bans over time. Points indicate the number of monthly published paragraphs since 1996, while the line and the grey area indicate the loess smoothed trend with its 95% confidence interval.[10] The data show a clear trend. The coverage of smoking bans shortly increased to around 500 paragraphs per month in the late 1990s, reached an all-time high in 2003 and another peak in 2007, after which it gradually decreased to around 150 paragraphs per month towards the end of the period. Moreover, in most newspapers coverage was intense in the period prior to the introduction of federal or statewide smoking bans, peaked when legislation was passed, and then decreased.[11] Further, the peak in the late 1990s correlates with California's extension of the smoking bans to bars, making it the first US state to enact a complete ban in all enclosed workplaces. Overall, reports on smoking bans in the US spiked again at the end of 2003, which is likely related to the introduction of a statewide smoking ban for all enclosed workplaces in New York, closely followed by the very similar Smoke-Free Air Act in New York City. From 2004 until 2007, finally, several states in our sample introduced state-wide smoking bans (e.g., Connecticut, Rhode Island, District of Columbia, New Jersey, Colorado, Utah, and Minnesota). It seems plausible that US newspapers paid particular attention to the two highest-profile anti-smoking policies of the last two decades. Overall, it is encouraging for the external validation of our supervised classification that the development of US newspapers' coverage on smoking bans seems to mirror the proposition, debate, and introduction of major legislative acts. Because our newspaper sample will eventually cover all US regions, we are confident that all major legislative activity related to smoking bans will be covered.

4.2 The perception of smoking bans: topic models

We present here the results of a model assuming 20 topics, taking into account the variables described in Section 3.2 and spatial lags based on geographic neighbors. Table 2 shows the top-50 words associated with each topic, along with labels that we determined based on those words. The interpretation of most topics is relatively straightforward and their connection with smoking bans quite clear.

[10] The development of the number of relevant articles over time (not shown) is very similar to the trends in Figure 1.

[11] Figures for each newspaper are presented in the Appendix ??. The Minnesota Star Tribune represents an exception to the general trend, as its coverage correlates with the non-smoking ordinance in Minneapolis, adopted and implemented in 2005.

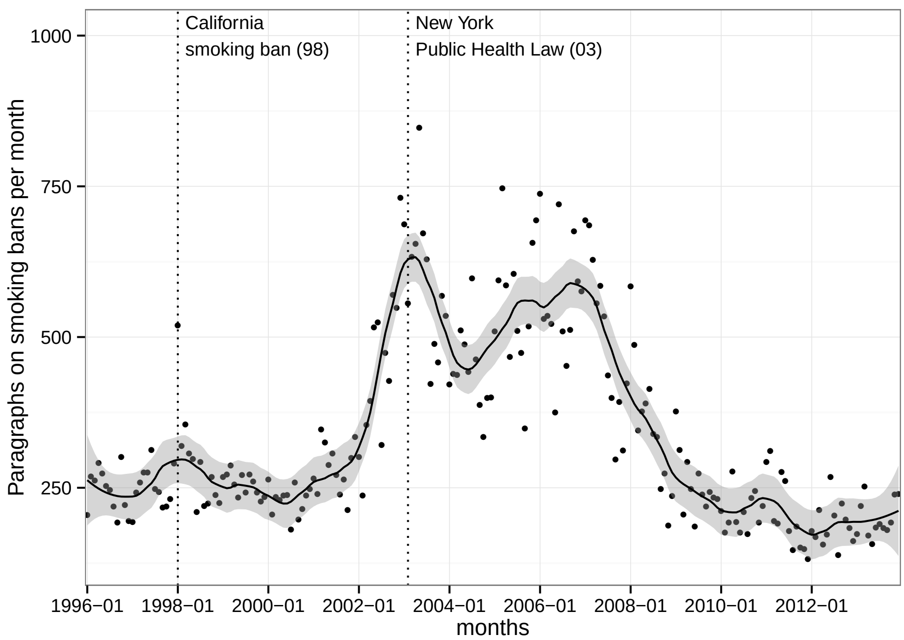

Figure 1: *Coverage of smoking bans in US newspapers.*

Benchmarking is a very interesting topic, directly related to the idea of policy diffusion. It identifies paragraphs relating specific smoking bans with broader trends in this area. *Decision-making process* picks up texts on various aspect of decision-making, including public opinion, hearings, and ballots. *Enforcement* focuses on the way smoking bans are enforced. *Freedom* refers to debates on the tension between smoking bans and individual choice. *Gambling* picks up discussions on the consequences of smoking bans for casinos and the gaming industry more generally. *Health* clearly refers to texts on the health consequences of smoking. *Legislation* is a straightforward topic referring to the enactment of smoking bans. *New York City* picks up reporting on smoking bans in New York City. *Regulations* refers to discussions of the specific rules implied by smoking bans. *Schools & colleges* discusses smoking restrictions in these settings. All these topics are clearly related to smoking bans and make intuitive sense.

A second set of topics is also coherent but more loosely connected with smoking bans. *Elections* is a topic clearly connected with events in electoral processes where smoking bans might have played a role. *Fires* is likely a residual category due to our broad keyword search. *Law & order* is at first sight loosely related to smoking bans, but it likely picks up incidents in the context of (drunken) people smoking outside of bars and clubs. *Lifestyle* is likely another residual category. *Localities I and II*

Benchmarking	*ban, smoke, restaur, state, public, smokefre, place, effect, includ, citi, year, workplac, associ, bar, antismok, restrict, percent, prohibit, law, california, statewid, indoor, group, local, enact, pass, communiti, chicago, last, similar, support, area, accord, alreadi, nation, illinoi, survey, will, first, adopt, american, month, number, sinc, now, mani, across, went, com, advoc*
Decision-making process	*citi, council, ban, ordin, propos, vote, member, issu, court, meet, approv, public, board, will, health, support, pass, hear, smoke, measur, rule, tuesday, committe, judg, mayor, attorney, councilman, decis, group, voter, whether, week, discuss, monday, ask, last, metro, offici, want, take, plan, loui, consid, decid, challeng, ballot, louisvill, lawsuit, petit, includ*
Elections	*mayor, polit, campaign, elect, presid, democrat, year, former, republican, citi, member, support, offic, term, run, issu, candid, parti, leader, public, district, first, clinton, also, council, critic, two, posit, voter, governor, race, time, last, repres, call, administr, seat, william, aid, interest, win, hall, made, power, major, congress, reform, serv, push, announc*
Enforcement	*cigarett, law, tobacco, fine, rule, smoker, enforc, use, violat, state, light, smoke, product, store, sale, new, sign, minor, regul, sell, legal, prohibit, advertis, illeg, machin, requir, will, restrict, alcohol, also, first, butt, public, offens, ban, warn, marijuana, face, shop, pack, limit, ashtray, within, penalti, age, make, vend, buy, compani, may*
Fires	*fire, area, park, photo, open, citi, street, burn, will, losangel, road, firework, downtown, restrict, grill, restaur, avenu, north, forest, use, water, santa, photograph, caption, mountain, south, east, near, patio, shop, west, close, time, feet, cafe, build, also, nation, lunch, place, land, dri, lake, outsid, hill, saturday, illustr, locat, allow, yes*
Freedom	*smoke, smoker, right, nonsmok, peopl, ban, busi, restaur, will, govern, choic, public, issu, make, mani, place, want, person, other, smokefre, free, reason, choos, freedom, may, believ, allow, forc, section, decis, concern, temp, whether, decid, individu, eat, letter, environ, breath, fact, citizen, establish, let, howev, respons, argument, enjoy, without, habit, major*
Gambling	*casino, revenu, game, gambl, state, percent, year, delawar, slot, machin, million, ban, citi, newjersey, atlant, nevada, will, video, smoke, last, oper, month, industri, floor, drop, lotteri, track, tax, vega, new, loss, las, resort, pennsylvania, bingo, declin, sinc, down, gambler, play, racetrack, fall, economi, two, bet, busi, lost, money, sale, three*
Health	*health, smoke, secondhand, air, protect, studi, public, hospit, cancer, worker, tobacco, american, lung, report, caus, risk, clean, employe, heart, diseas, children, research, smokefre, depart, danger, work, indoor, exposur, societi, year, level, medic, percent, prevent, general, show, peopl, associ, industri, found, expos, death, pollut, also, breath, workplac, control, harm, evid, hazard*
Law & order	*polic, car, offic, fire, prison, inmat, charg, told, two, jail, offici, depart, driver, call, gun, report, drive, correct, investig, man, phone, street, case, tri, drug, kill, hour, home, month, arrest, day, complaint, use, court, sheriff, secur, vehicl, crimin, three, cell, time, sever, found, safeti, last, crime, took, outsid, train, left*
Legislation	*bill, state, legisl, ban, senat, hous, vote, pass, committe, law, legislatur, lawmak, smoke, measur, support, statewid, propos, sen, year, public, approv, gov, rep, assembl, sponsor, will, allow, amend, session, governor, local, last, sign, exempt, govern, issu, leader, debat, introduc, week, capitol, lobbyist, includ, major, make, chang, democrat, repres, act, general*

Lifestyle	*like, peopl, just, get, say, think, want, now, time, come, make, know, even, thing, way, see, tri, take, good, work, still, look, lot, much, place, outsid, back, realli, around, someth, ask, might, away, will, day, seem, need, feel, put, mani, littl, tell, never, keep, happen, live, chang, differ, find, everi*
Localities I	*counti, maryland, commission, howard, charl, montgomeri, paul, execut, minnesota, baltimor, last, offici, height, year, villag, georg, minneapoli, washington, virginia, district, will, region, week, columbia, jurisdict, princ, lake, hennepin, month, loui, supervisor, take, two, arlington, duncan, govern, communiti, robey, yesterday, ann, countywid, ramsey, friendship, coalit, kelli, omalley, bloomington, unincorpor, three, measur*
Localities II	*town, board, beach, health, boston, regul, meet, last, will, communiti, resid, massachusett, week, public, offici, south, street, local, kanawha, rhodeisland, north, director, may, main, east, new, hear, portland, charleston, year, globe, depart, butt, burlington, putnam, consid, plan, month, recent, also, two, neighbor, cambridg, april, west, connecticut, dog, region, yesterday, control*
New York City	*newyork, citi, bloomberg, countri, world, govern, nation, will, new, ban, year, pub, public, american, mani, cultur, unit, mayor, last, ireland, offici, manhattan, war, fat, michael, franc, europ, first, forc, cuba, group, america, european, food, drink, tran, trade, now, time, foreign, even, protest, part, intern, french, minist, cuban, recent, month, news*
Obituary I	*year, member, serv, school, home, univers, work, retir, church, servic, will, famili, son, wife, die, husband, graduat, memori, also, funer, born, daughter, high, surviv, associ, war, presid, brother, hospit, sister, former, move, love, club, friend, colleg, two, degre, attend, includ, board, grandchildren, death, world, john, visit, armi, mani, washington, citi*
Obituary II	*time, year, first, life, play, last, day, back, husband, man, work, took, went, friend, told, famili, mother, guy, home, two, left, father, love, job, stori, never, end, right, player, came, night, week, talk, coach, wife, cigar, knew, show, team, later, made, got, son, world, morn, live, alway, month, learn, rememb*
Property development	*build, citi, will, new, work, year, develop, tax, plan, resid, compani, properti, million, state, also, hous, job, busi, program, fund, money, servic, project, pay, cost, manag, unit, help, use, apart, home, local, worker, system, need, construct, provid, communiti, creat, offic, employe, oper, site, rais, hire, includ, center, group, move, neighborhood*
Regulations	*bar, smoke, restaur, busi, owner, allow, custom, establish, law, will, area, exempt, club, room, licens, patron, ban, food, privat, tavern, separ, new, liquor, serv, effect, also, ventil, permit, sale, cigar, bowl, manag, percent, employe, alcohol, dine, complaint, seat, appli, hotel, drink, requir, post, two, alley, compli, loung, hall, lose, pub*
Schools & colleges	*smoke, park, school, will, area, polici, student, build, univers, board, campus, public, outdoor, high, design, allow, facil, colleg, offici, properti, prohibit, includ, center, use, new, staff, district, recreat, also, ban, feet, ground, tobacco, outsid, within, event, field, employe, educ, georgia, hall, atlanta, resid, villag, entranc, librari, class, offic, children, oklahoma*
Travel	*bar, flight, airport, room, hotel, cigar, place, night, airlin, new, air, passeng, music, travel, open, light, two, club, loung, intern, line, call, seat, street, first, tabl, plane, beer, restaur, includ, crowd, band, danc, wine, hour, drink, year, glass, island, cruis, wall, space, old, offer, fli, art, show, guest, set, spot*

Table 2: *Top-50 words for each topic.*

mention various cities and towns, but the connection with smoking bans is not immediately apparent. *Obituary I and II* might show up because the texts mention cancer. *Property development* is probably a residual category, like *Travel*.

The presence of residual topics is not necessarily a problem. In fact, they are to be expected, given that our filter could not remove all irrelevant texts. These topics identify texts that are not relevant for our purposes and that we therefore can ignore. We conclude from Table 2 that our model identifies relevant and meaningful topics, surprisingly so considering that they were produced purely inductively, without human input.

Figures 2–7 show estimated topic prevalence as a function of five variables included in the STM: month dummies, the presence of a smoking ban in a state (0 before enactment, 1 after enactment), a dummy for the month in which the ban was enacted, the number of months before enactment (up to six months), the number of months after enactment (up to six months), and the percentage of neighboring states that have enacted a smoking bans. Importantly, the variables in Figures 3–7 consider smoking bans in bars. The STM includes the same variables accounting for bans in six other areas. The corresponding figures are shown in Appendix A2. The figures show the estimated prevalence of all topics. Red lines denote topics that we find particularly relevant for the purposes of this paper. Our interpretation focuses on them. Finally, we note that, because our model assumes 20 topics, baseline topic prevalence is 0.05.

Figure 2 shows the estimated topic prevalence as a function of time. The trends are irregular because they are estimated with monthly dummies with no smoothing, but their purpose is not primarily substantive. Instead, the month control for unobserved events affecting all units. That said, a few patterns are interesting. The markedly punctuated trend for *Legislation* is consistent with infrequent but important law-making at the state level. The downwards trend of *Freedom* after 2005 is noteworthy: the implications of smoking bans for individual choice have progressively become less relevant, consistent with the idea that the policy now enjoys broad acceptance. *Regulations* also displays a sharp downwards trend since 2008, meaning that the specific details of smoking bans have been less intensely discussed than they previously were. This might indicate that they have become less controversial. *Gambling*'s relevance increases sharply after 2008, as casinos became more affected by smoking restrictions. Finally, *Benchmarking*'s prevalence was high especially between 2002 and 2010, during the phase of smoking ban's expansion throughout the country.

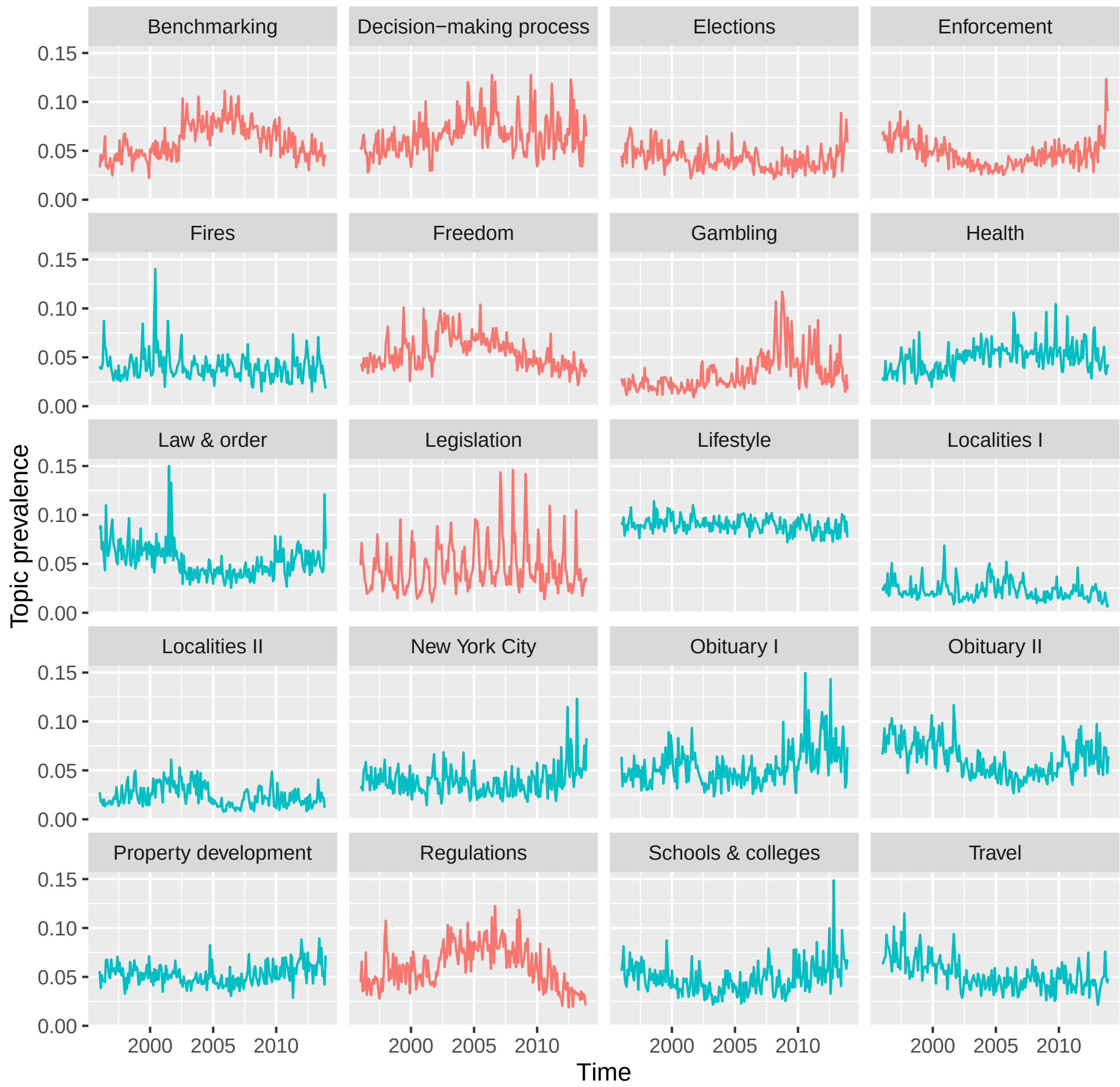

Figure 2: *Estimated topic prevalence as a function of time. Red lines denote the most interesting topics.*

Figure 3 shows that *Benchmarking* is less prevalent after a smoking ban has been enacted than before. This pattern is even stronger for *Decision-making process*, implying that, quite plausibly, decision-making activity decreased after the enactment of smoking bans. *Freedom* follows the same pattern, which means that the implications of smoking bans for individual choice became less controversial after people could experience the policy. Figure 4 shows which topics were more prevalent in the month in which smoking bans were enacted. The spike in *Legislation* is unsurprising but excellent news for the validity of our model: it identifies, very plausibly, that newspapers had more stories on legislative activity when such activity actually occurred. *Benchmarking* is also slightly more prevalent at these moments, possibly because, when legislation is discussed, it is compared with the practices of other

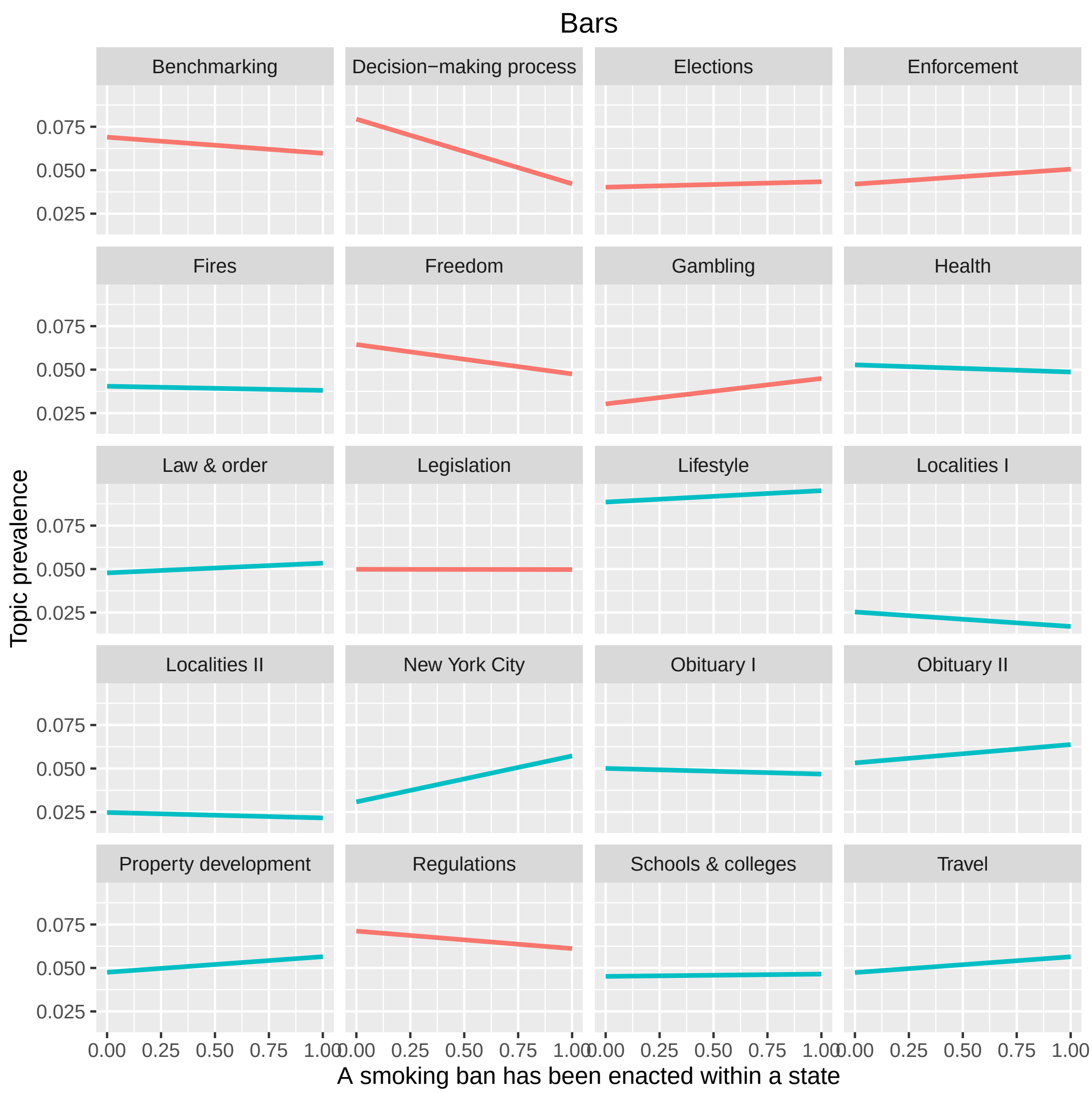

Figure 3: *Estimated topic prevalence as a function the presence of a smoking ban in bars within a state. Red lines denote the most interesting topics.*

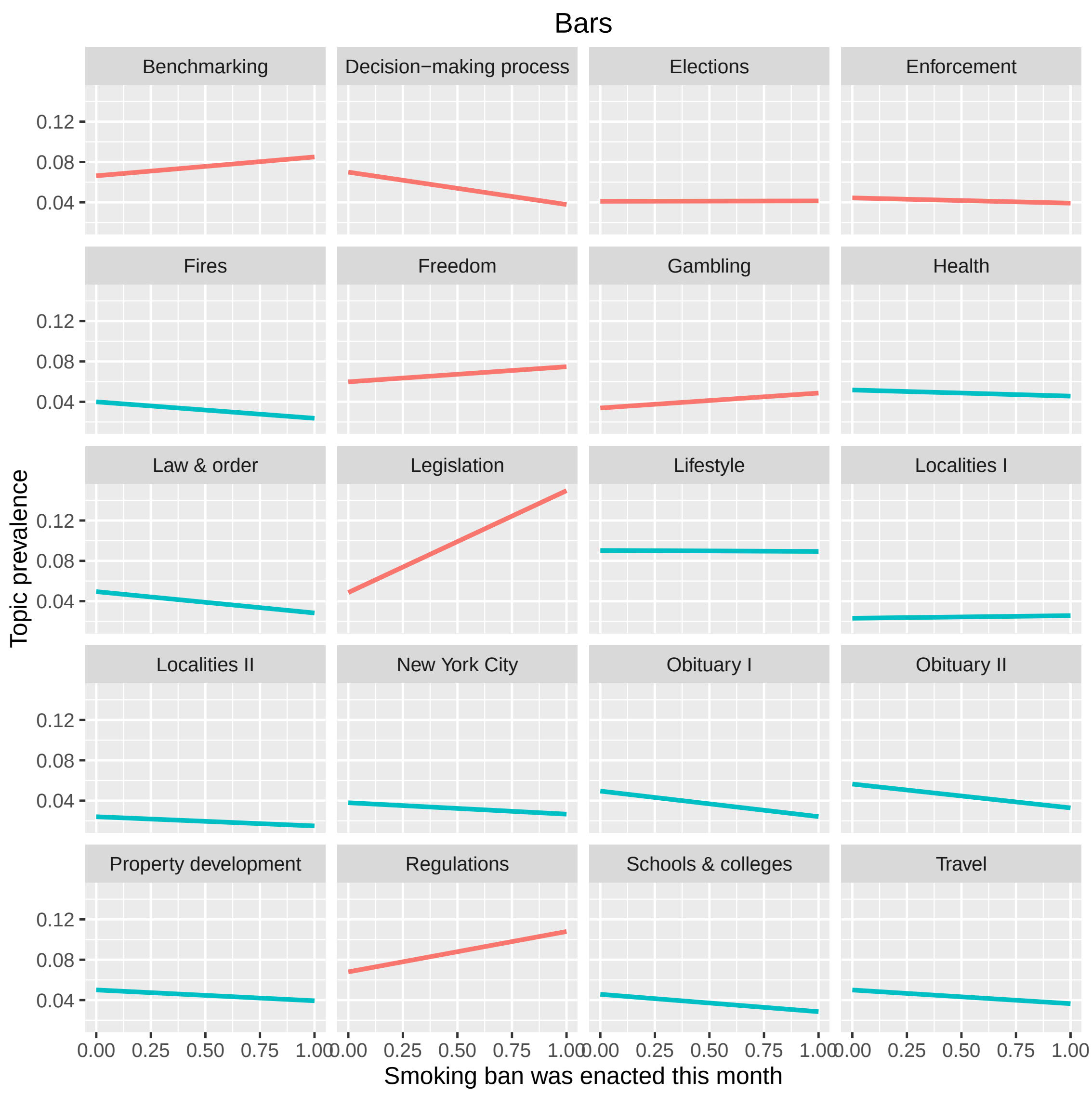

Figure 4: *Estimated topic prevalence as a function of the enactment of a smoking ban in bars, in a given month and within a state. Red lines denote the most interesting topics.*

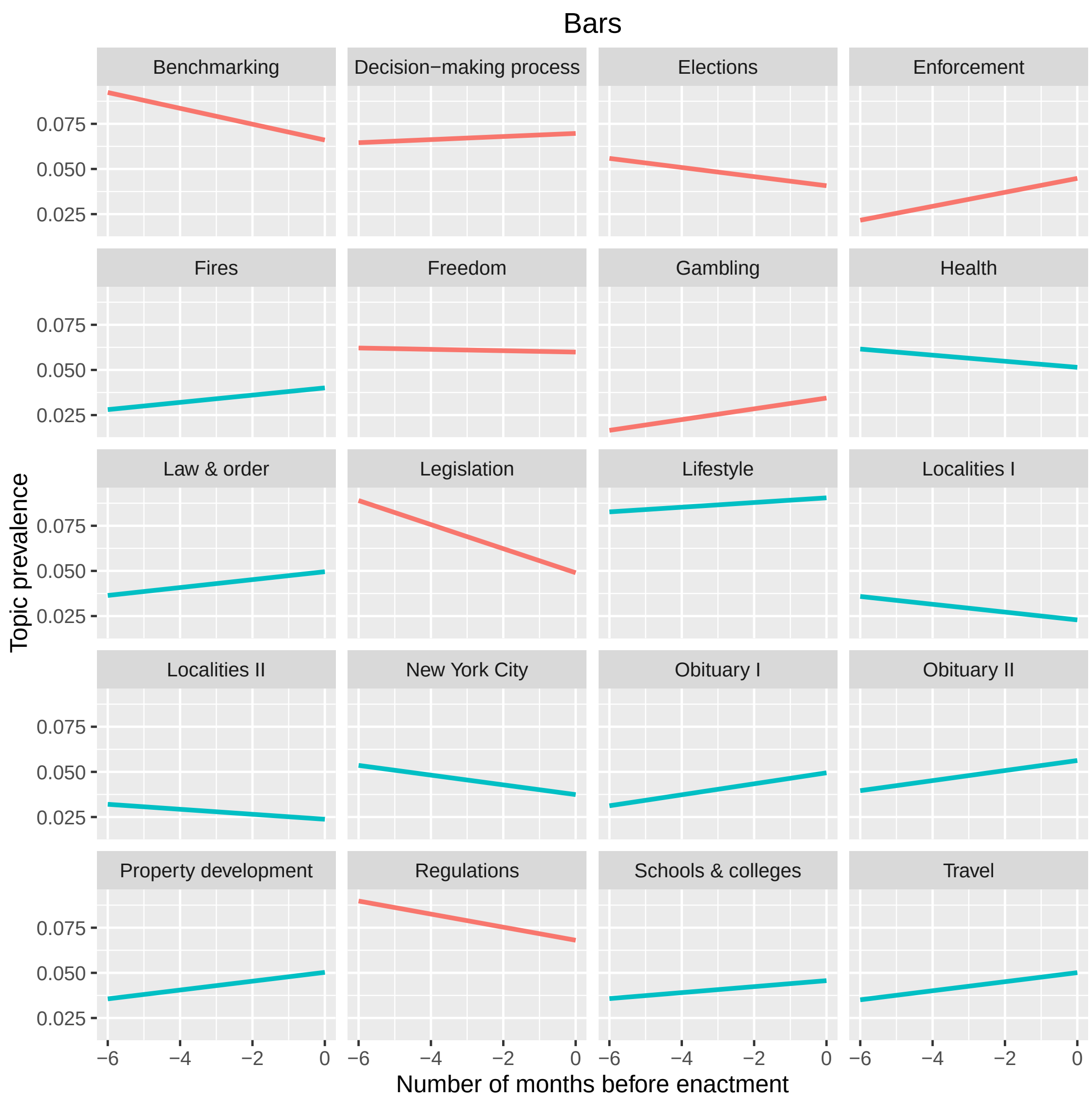

Figure 5: *Estimated topic prevalence as a function of the number of months before the enactment of a smoking ban in bars within a state. Red lines denote the most interesting topics.*

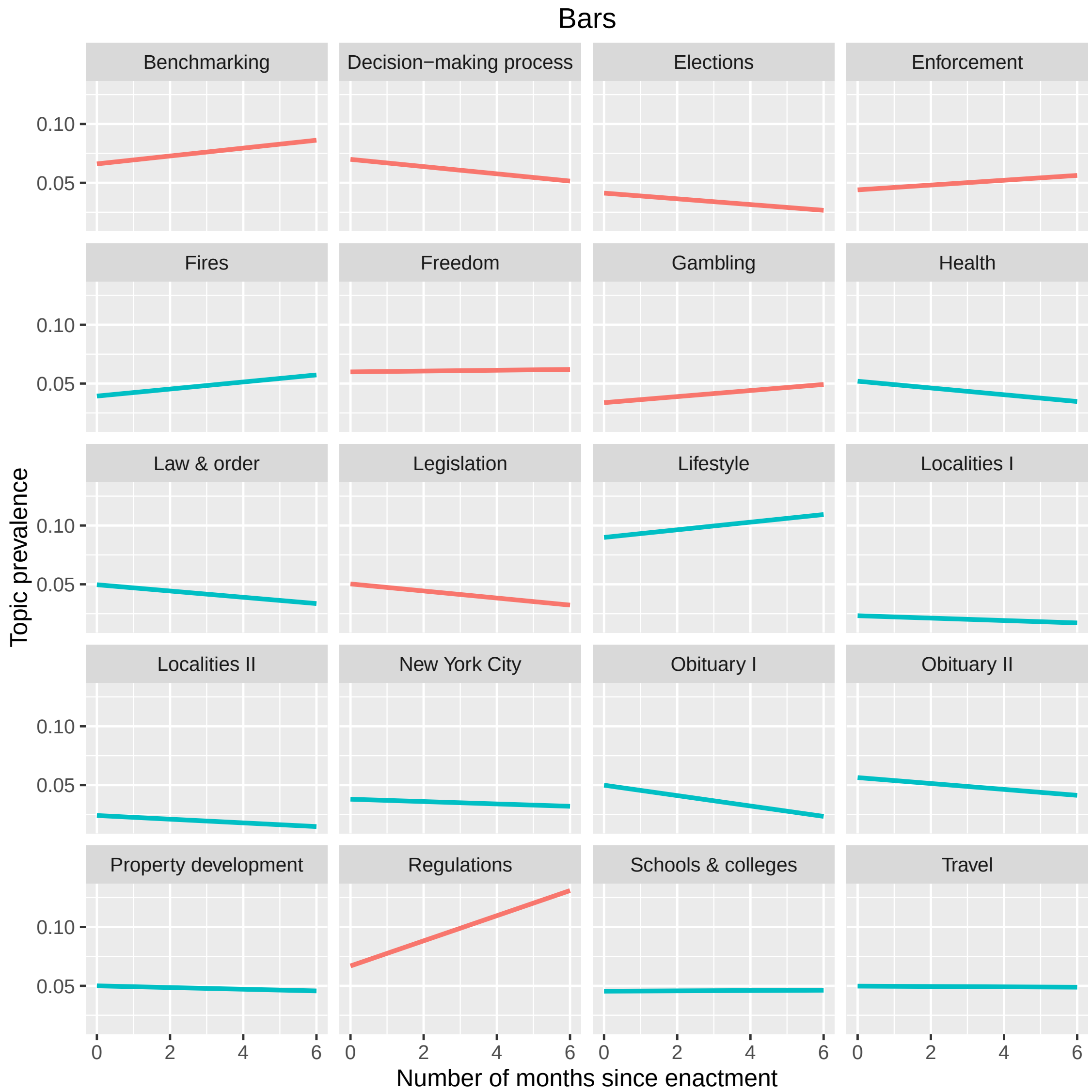

Figure 6: *Estimated topic prevalence as a function of the number of months since the enactment of a smoking ban in bars within a state. Red lines denote the most interesting topics.*

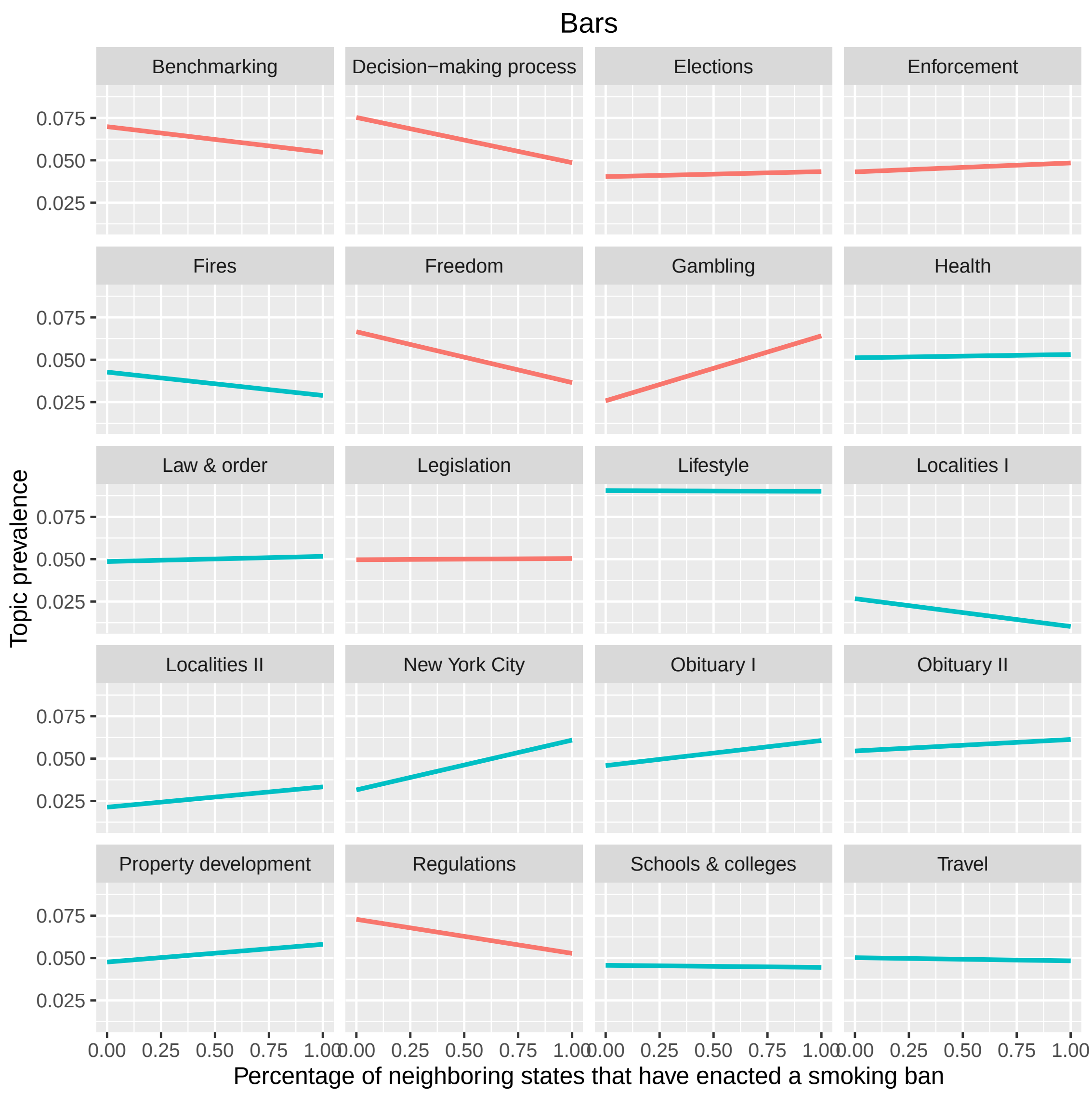

Figure 7: *Estimated topic prevalence as a function the percent of neighboring states with a smoking ban in bars. Red lines denote the most interesting topics.*

states or with nation-wide trends. Figure 5 shows that both *Benchmarking*'s and *Legislation*'s prevalence decreases in the six months leading to smoking bans' enactment. This likely reflects the schedule of the law-making process, with a time lag between decisions in House and Senate and the formal enactment of the policy. We will explore this aspect more in depth in future versions. Figure 6 shows that both the details of the law *Regulations* and its enforcement (*Enforcement*) become more prevalent in the months after enactment. This pattern is consistent with the focus shifting to implementation after the policy has been introduced.

Finally, in Figure 7 we provide initial evidence of the relationship between the topics and earlier policy enactments on other states—that is, the central argument of this project. Surprisingly, *Benchmarking*'s prevalence decreases as more neighboring states adopt smoking bans. *Decision-making process* follows the same pattern, which might mean that decision-making processes become less controversial when more states already have enacted the policy. The pattern of *Freedom* is striking: the implications of smoking bans for individual choice are much more debated when a state is among the first to adopt the policy, suggesting that, as smoking bans spread, this aspect is no longer perceived as central. The specific details of smoking restrictions *Regulations* also seem to lose relevance as more examples become available. By contrast, the consequences of smoking bans for casinos *Gambling* gain salience when other states have enacted them.

We hasten to add that at this point we need to be cautious and not read too much into these figures—we are, after all, simply showing correlations and then constructing explanations that are consistent with the correlations that we see. Moreover, the figures are based on work in progress. The results are bound to evolve. Still, several findings emerge from these figures. First, there are clearly different types of policy perceptions that emerge in the media coverage of the debates and discussions about whether to adopt new policies. Second, there is variation across these perceptions we have identified, in terms of prevalence. Third, there is also variation within the topics. Some of these frames decrease in prevalence as a function of earlier adoptions; others increase; and others remain fairly flat. The more central and general point, though, is that the STM allows us to model topic prevalence as a function of policies in other states, which puts these policy perceptions directly in the overall diffusion process.

5 Conclusion

Policy diffusion is a multi-stage process, but most research has been limited to an examination of only two of these stages—the initial adoption (or adoptions) in some set of states, and then whether future adoptions are influenced by these earlier adoptions. We argue that an intermediary stage is of crucial importance, both because it is affected by earlier adoptions and because it can affect later adoptions. More specifically, it is during this intermediary stage—the second stage of the diffusion process—that states form specific perceptions of policies. These perceptions can plausibly influence the likelihood of adoption, but our interest in this paper is on examining these perceptions themselves. What perceptions exist? Do these perceptions vary over time? And most importantly, are these perceptions a function of earlier adoptions elsewhere? To the extent that these perceptions are a function of earlier adoptions, we should recognize them as a critical part of the overall diffusion process.

Our analysis provides a first step toward better understanding how policy perceptions can diffuse—or more accurately, how the first stage of the diffusion process, in which other states adopt policies, can influence the next stage, in which policy perceptions are formed. We have put forward a preliminary analysis of the diffusion of the perception of smoking bans in US states based on a structural topic model of over 72,000 paragraphs in thirty-eight newspapers, showing that there is variation in the incidence of these perceptions, as well as connections between these perceptions and the prevalence of prior adoptions in neighboring states.

Of course, much work remains to be done. In terms of data, the first step is to complete our newspaper sample. We also are in the process of collecting newspaper articles regarding the consideration of anti-smoking policies in Swiss cantons, which will provide for a useful comparison with the US states. We also are continuing to work on the topic models themselves, including improving the classifier used to weed out irrelevant texts, the use of Named Entity Recognition tools to identify states and cities in the texts, and a more careful consideration of time dependence. In addition, obtaining estimates of whether the newspaper coverage was positive or negative will allow us to ascertain whether not only the frame, but the nature of the frame, varies in response to earlier adoptions. The sentiment analysis we conducted (but not reported in detail) is first step in this direction. For improving both our classifier and the analysis of sentiment, we are considering the crowd-sourced approach put forward by Benoit et al. (2016), which could help us to drastically and efficiently increase the number of manual annotations needed to improve accuracy.[12] And finally, we can use our data to examine a range of other important questions—whether perceptions change within a state after it adopts a policy, for example, or how the relative prevalence of frames within a state changes over time. For now, however, our preliminary analysis has established a foothold for the usefulness of structural topic models and support for the idea that policy perceptions are an important part of the diffusion process.

[12]We thank Slava Mikhaylov for suggesting this strategy.

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A1 Topic model coherence

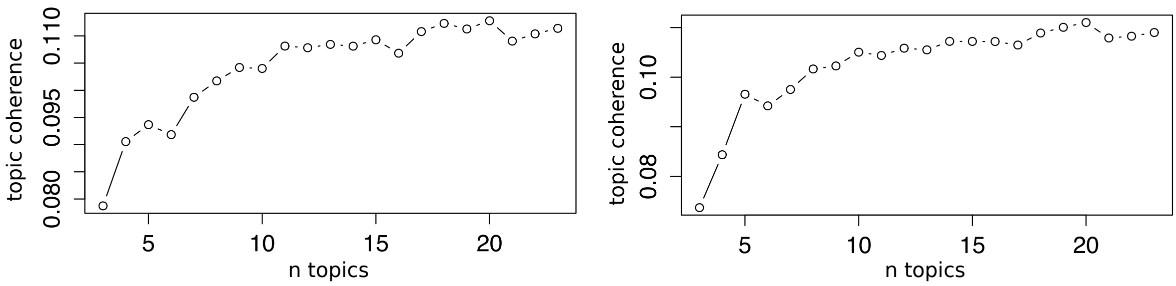
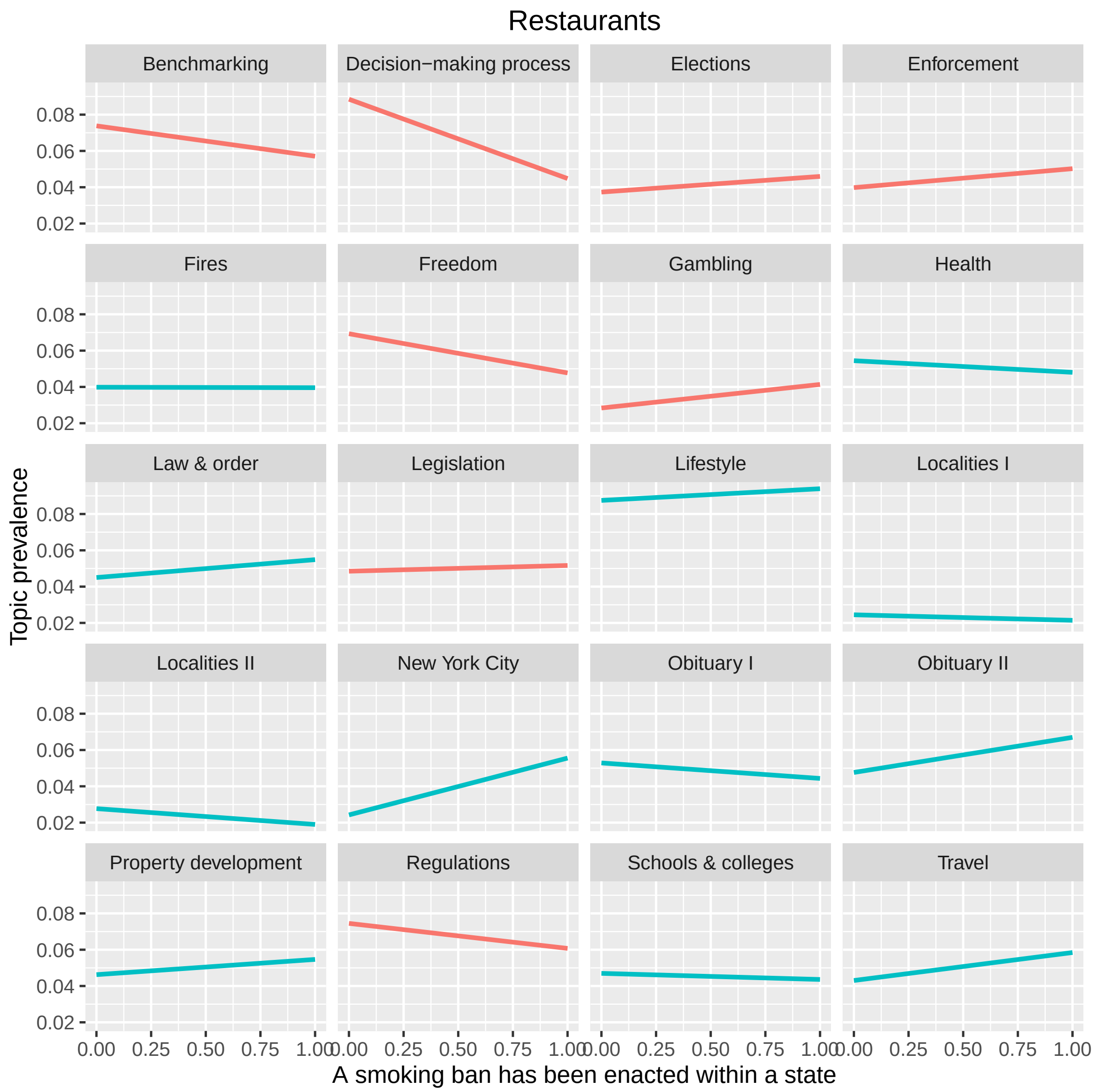
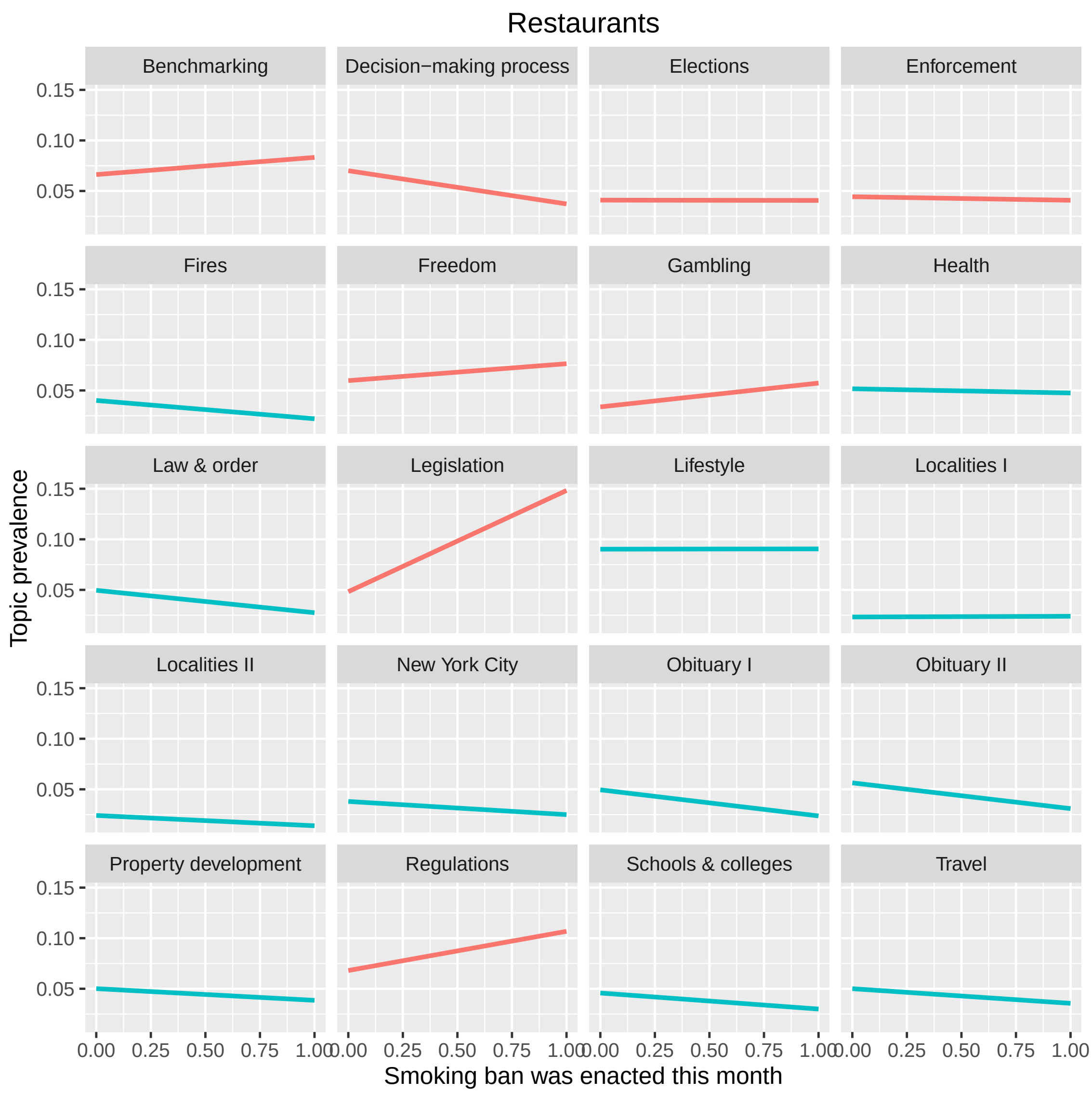


Table A1: *Word2vec topic coherence for 3-23 topics for the models including sptial lag based on geographical proximity (left) and highest influence (right).*

A2 Smoking bans in other areas




Restaurants
Benchmarking
Decision−making process
Elections
Enforcement
Fires
Freedom
Gambling
Health
Law & order
Legislation
Lifestyle
Localities I
Localities II
New York City
Obituary I
Obituary II
Property development
Regulations
Schools & colleges
Travel
Topic prevalence
0.15
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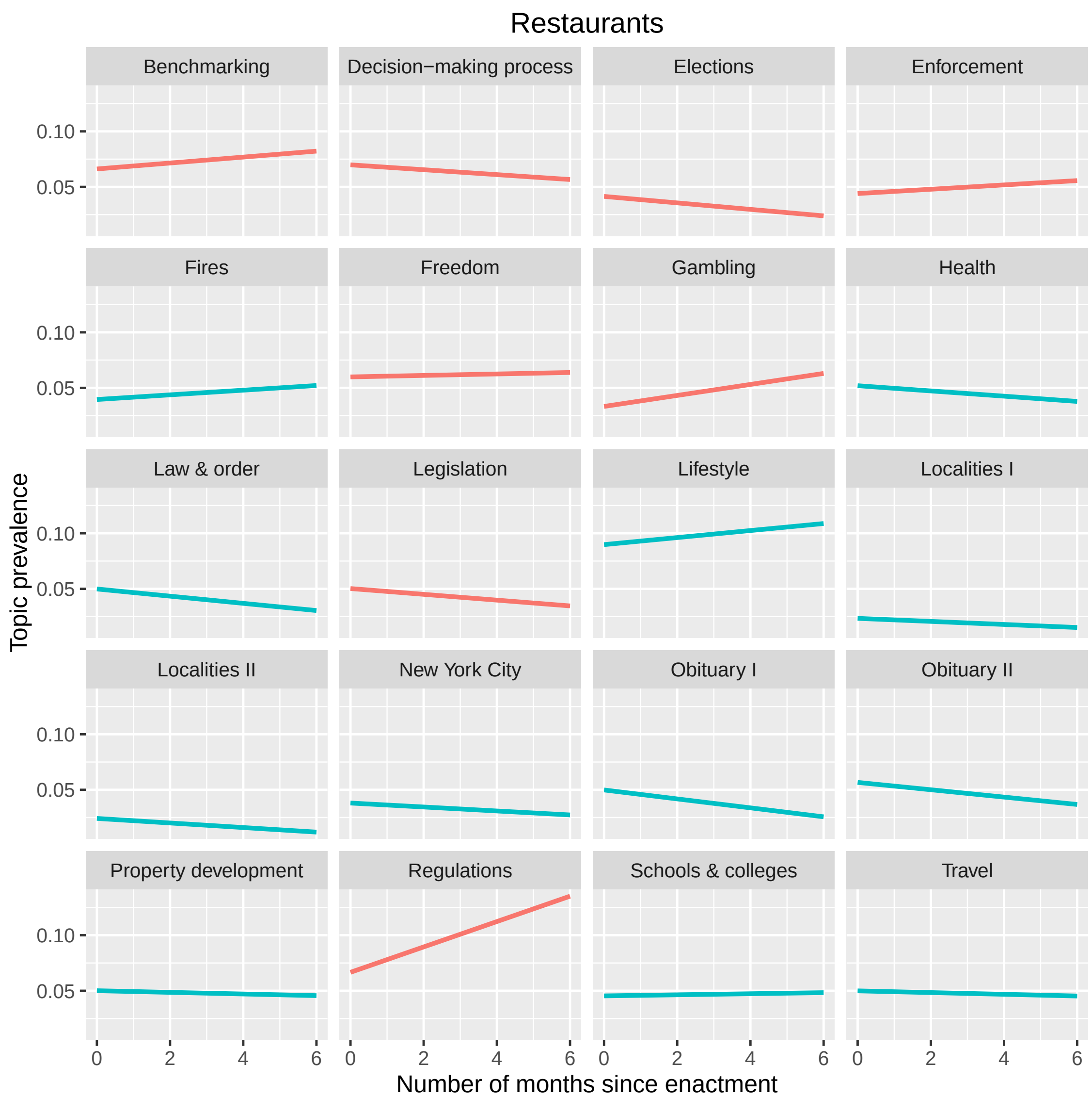
Smoking ban was enacted this month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Decision−making process
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Legislation
Lifestyle
Localities I
Localities II
New York City
Obituary I
Obituary II
Property development
Regulations
Schools & colleges
Travel
Topic prevalence
0.10
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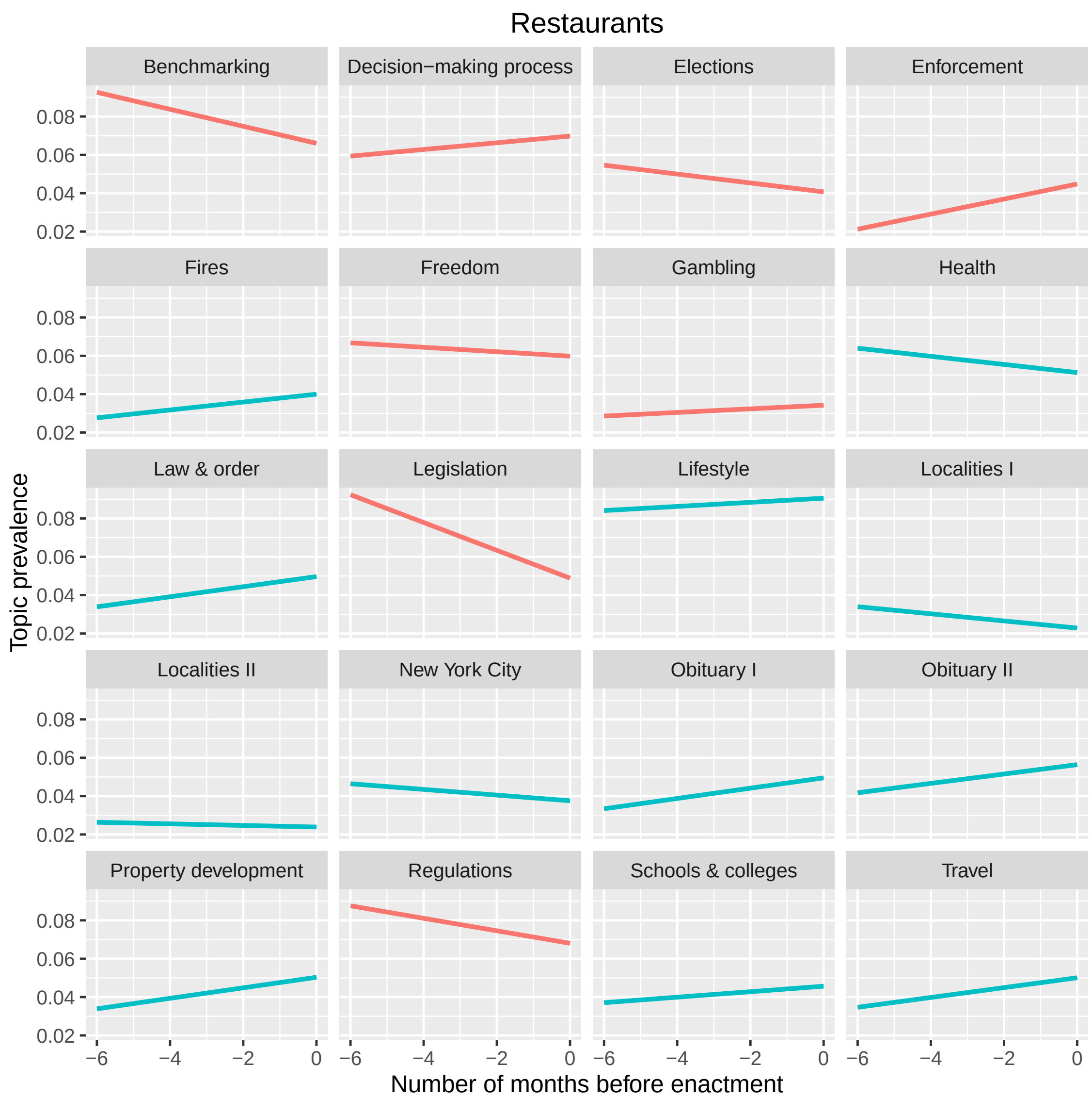
0
2
4
6
Number of months since enactment


Restaurants
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Localities I
Localities II
New York City
Obituary I
Obituary II
Property development
Regulations
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Topic prevalence
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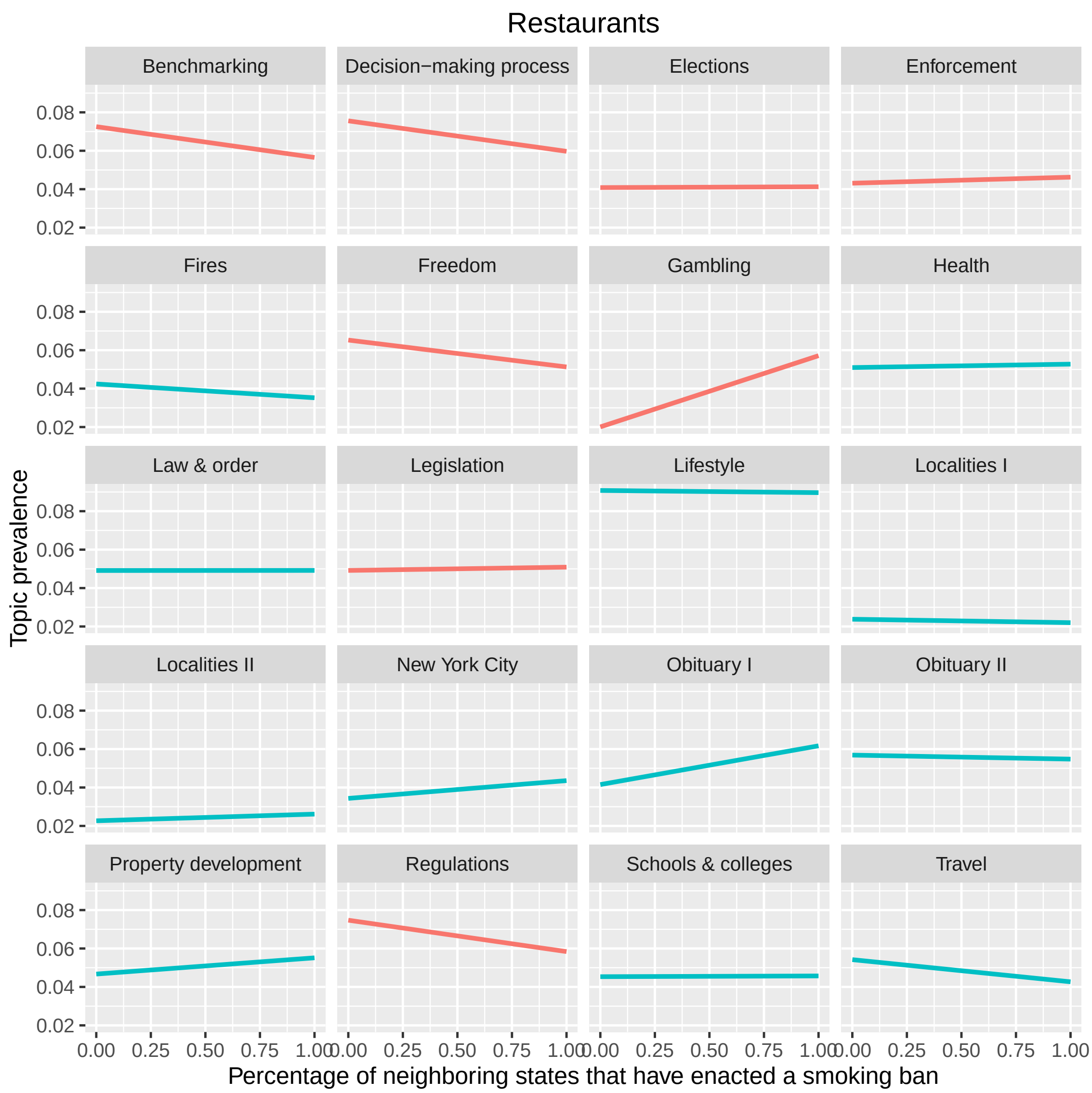
Number of months before enactment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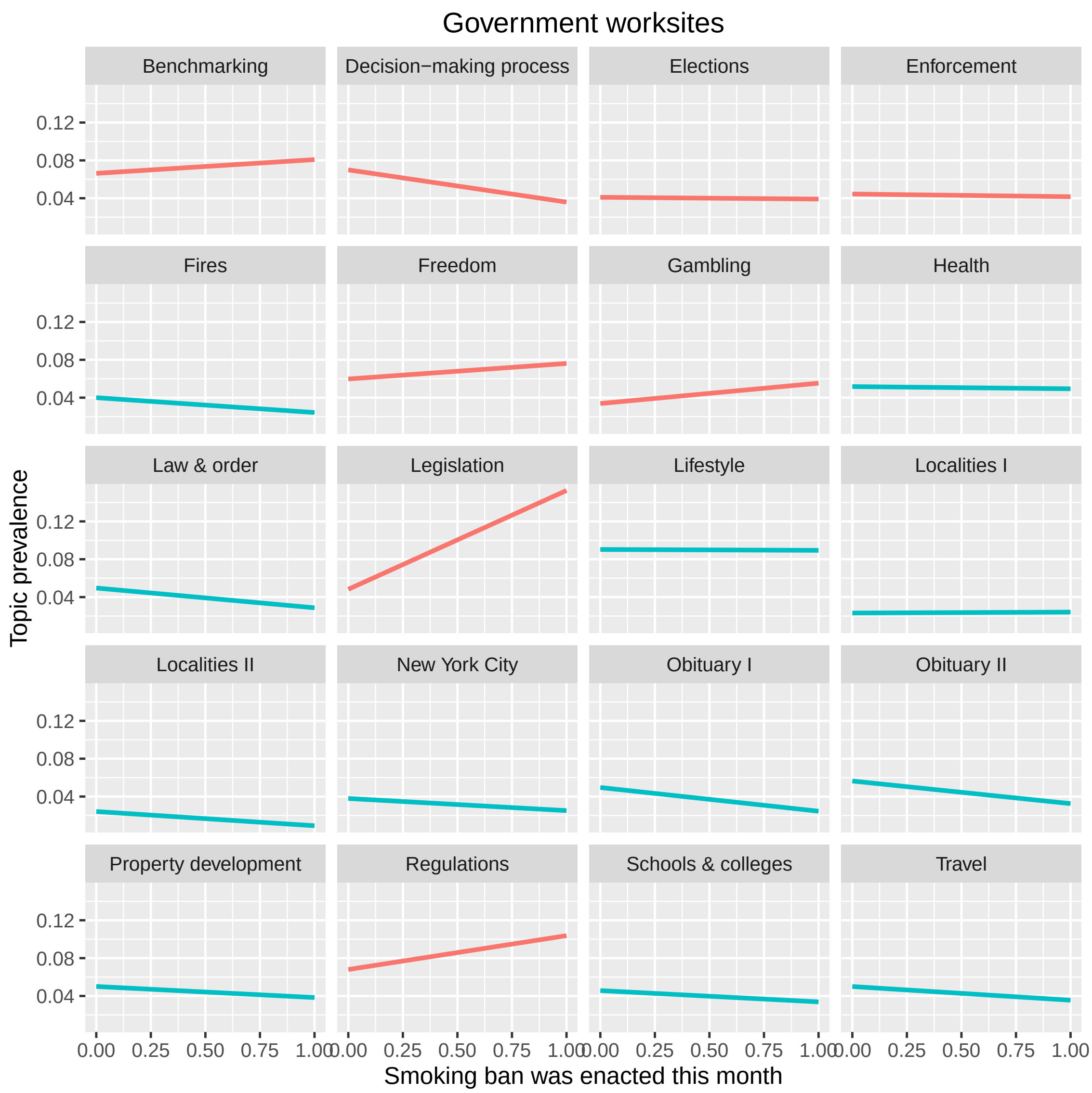
Percentage of neighboring states that have enacted a smoking ban



Government worksites
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Elections
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Freedom
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Localities I
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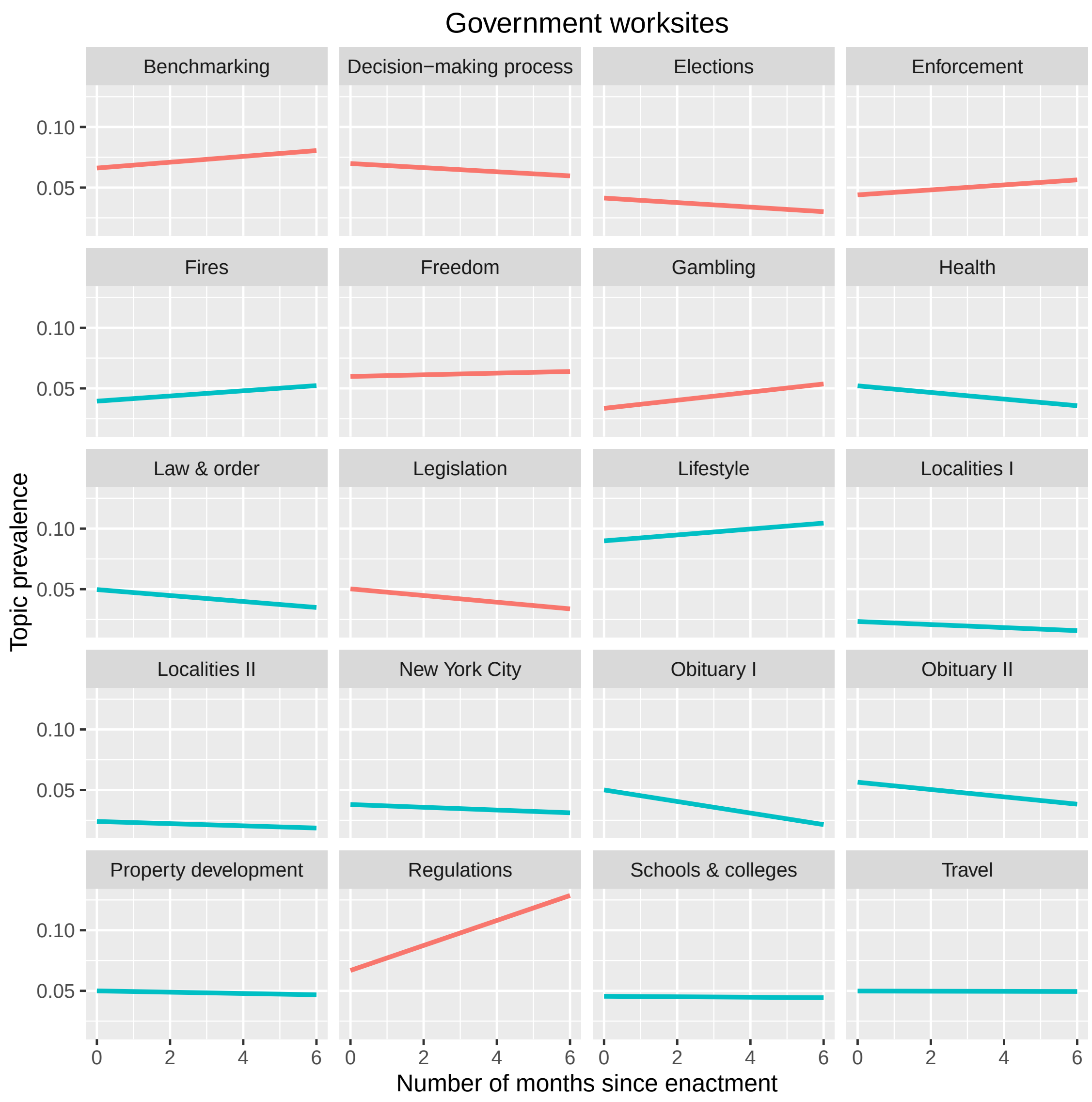

Government worksites
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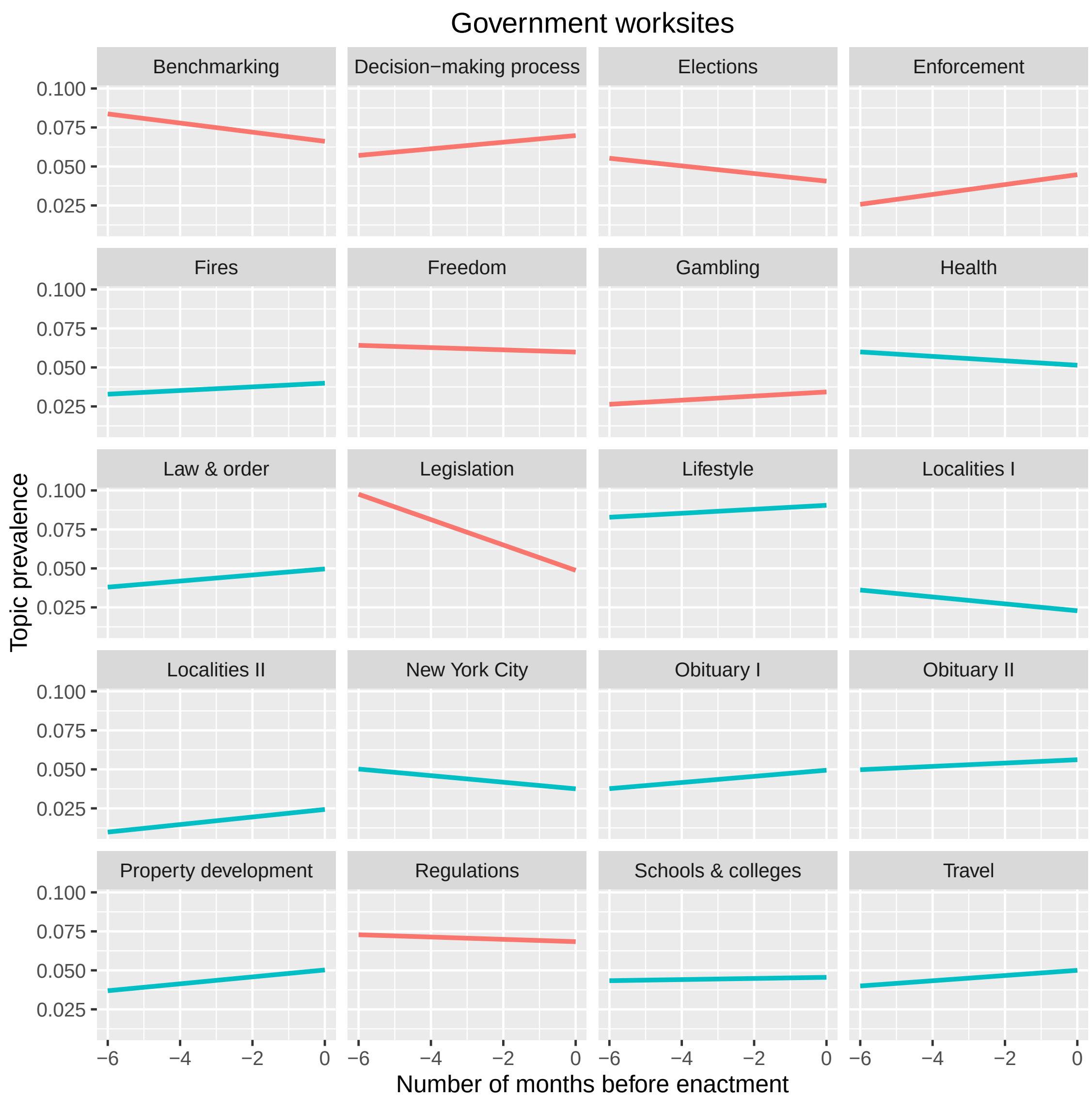
Number of months since enactment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Localities I
Localities II
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Property development
Regulations
Schools & colleges
Travel
Topic prevalence
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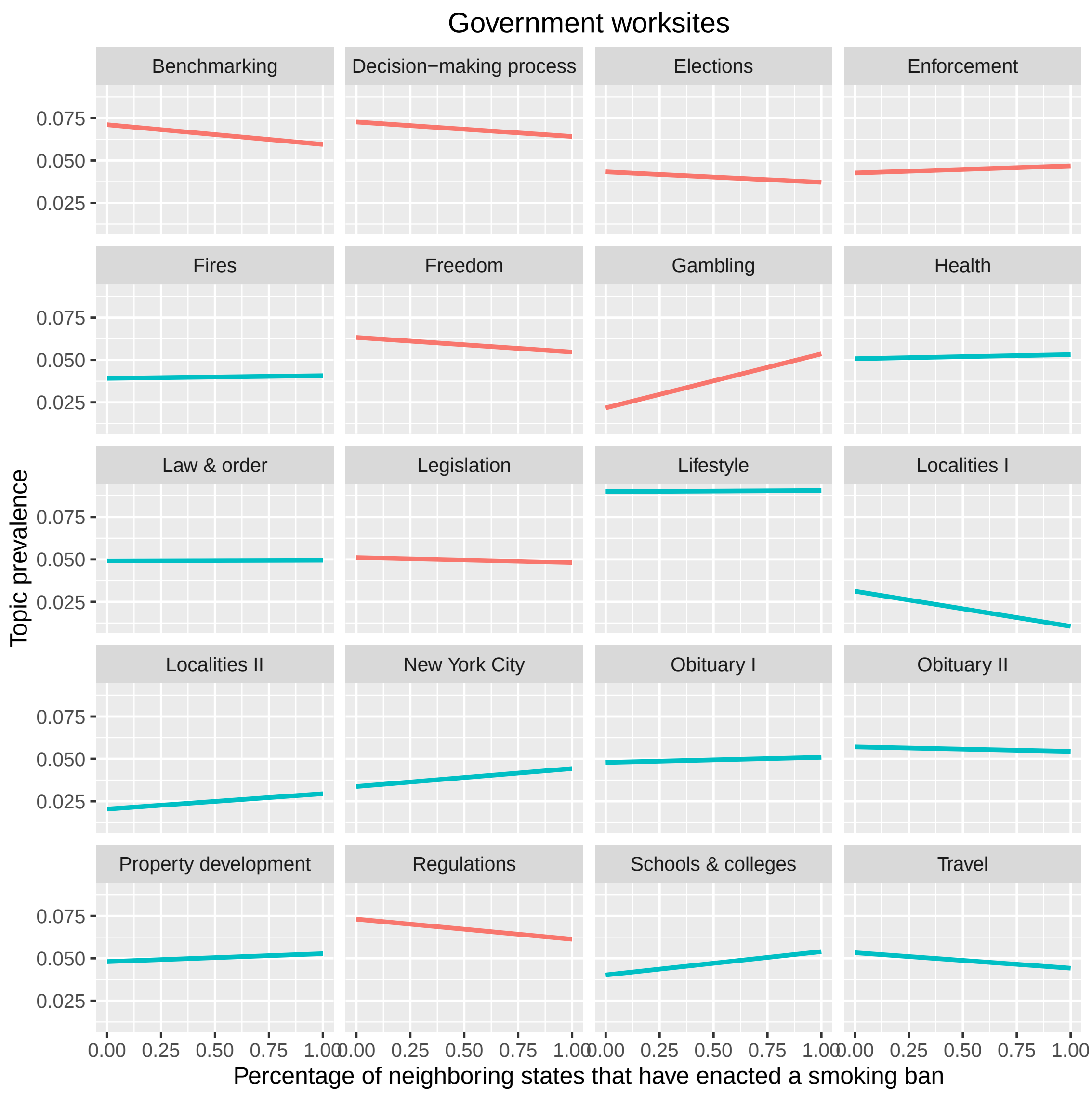
Number of months before enactment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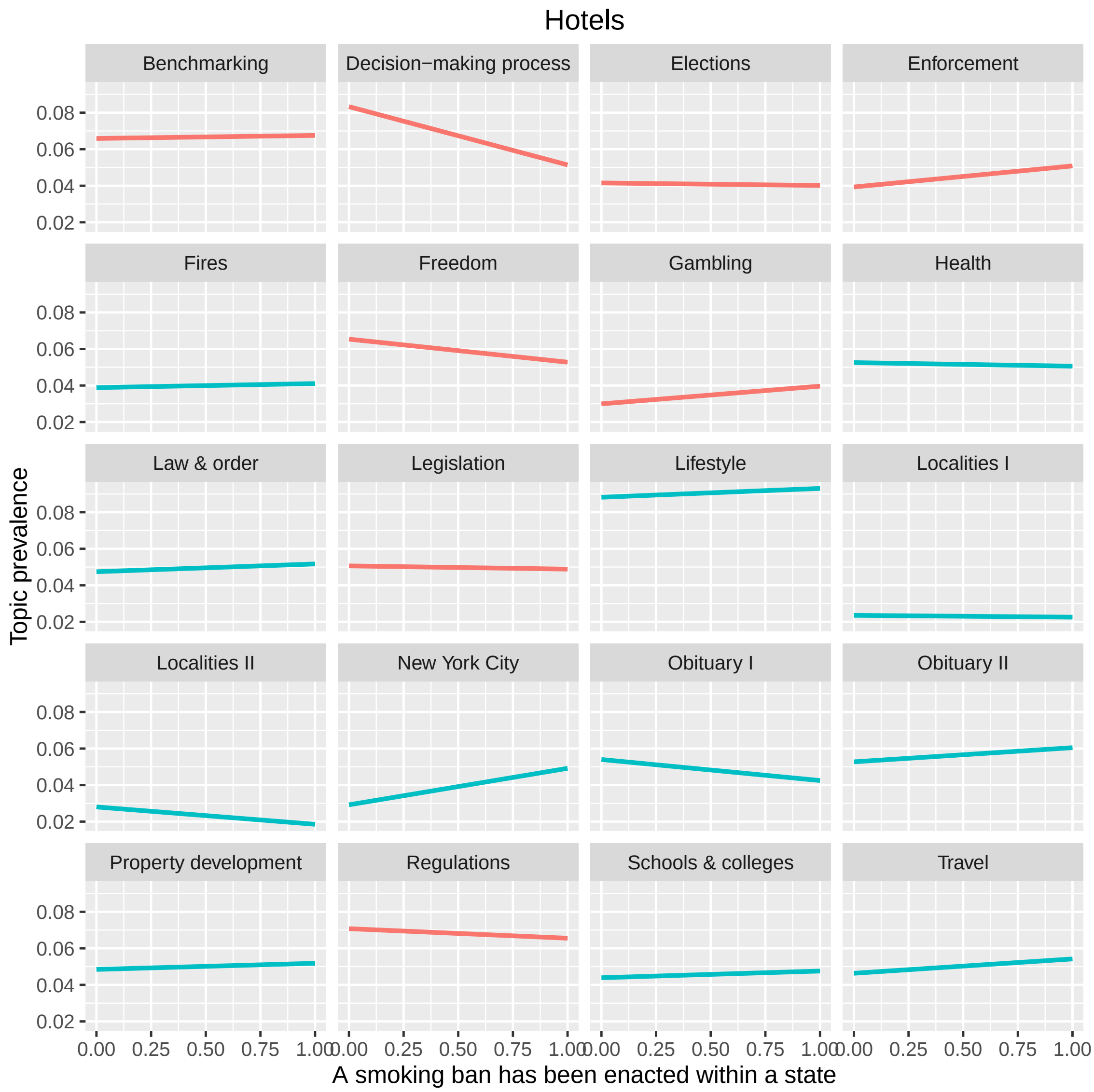
Topic prevalence
Percentage of neighboring states that have enacted a smoking ban


Hotels
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Schools & colleges
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Topic prevalence
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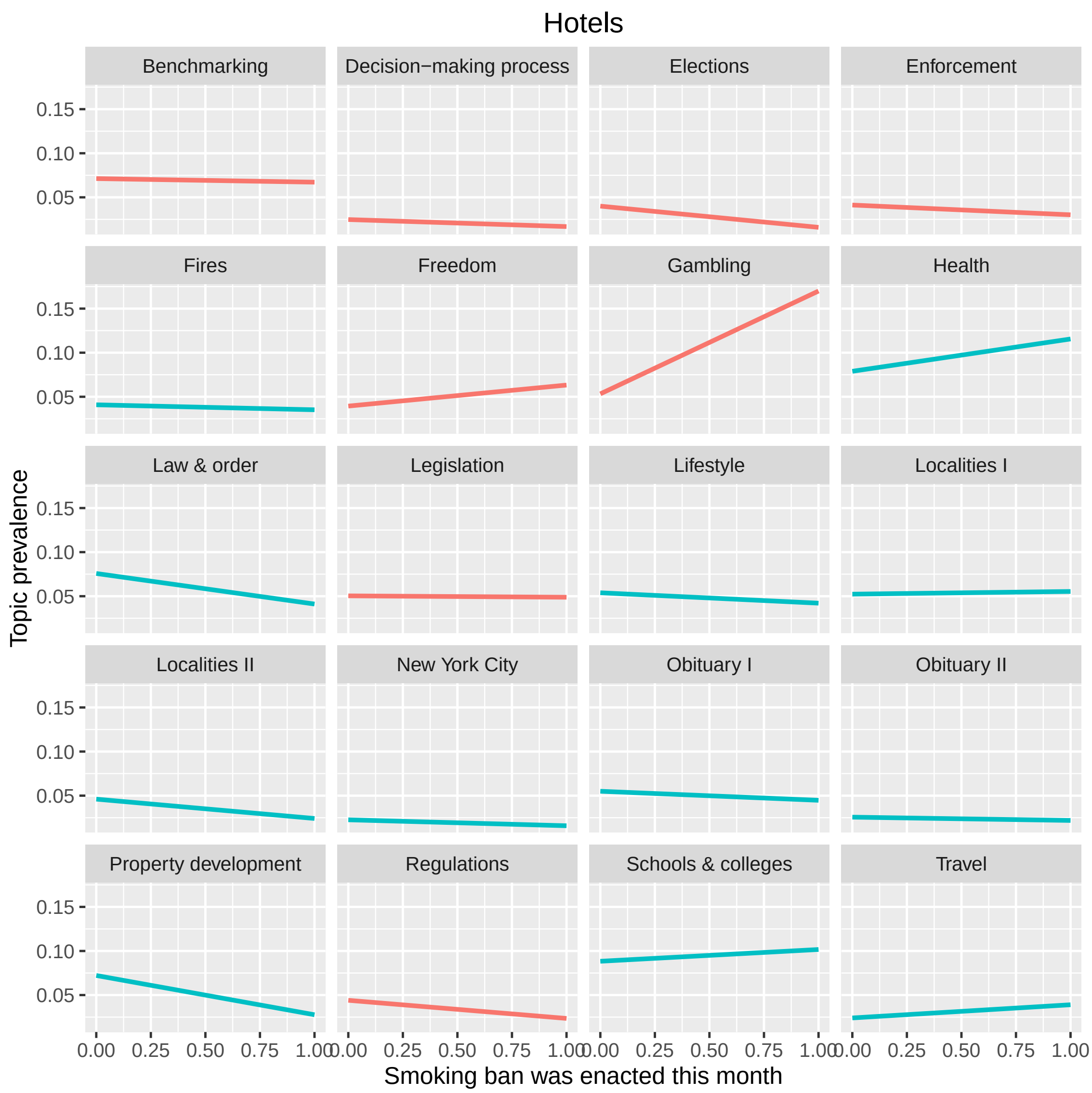
A smoking ban has been enacted within a state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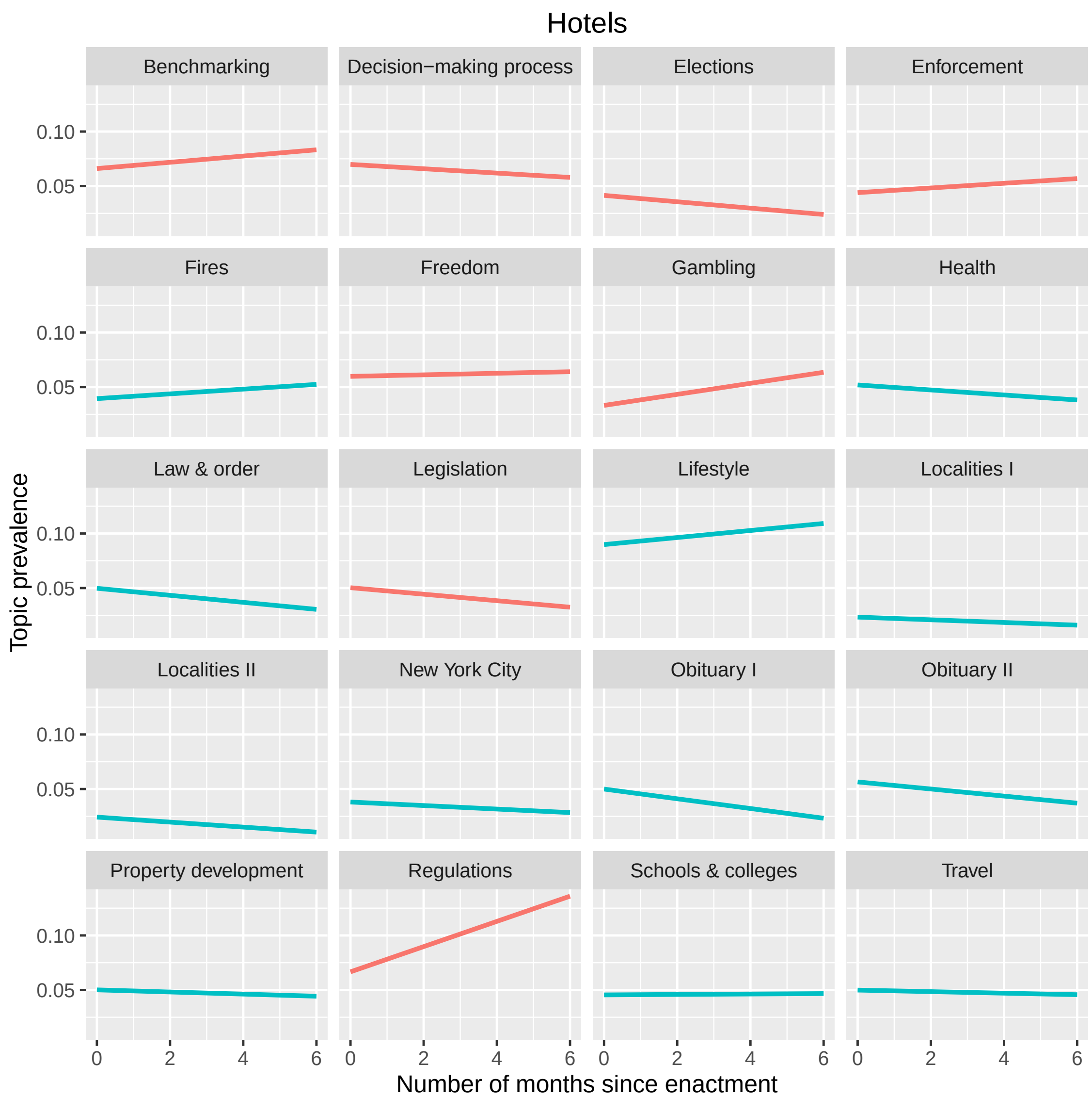
1.00
Smoking ban was enacted this month


Hotels
Benchmarking
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Elections
Enforcement
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Gambling
Health
Law & order
Legislation
Lifestyle
Localities I
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Obituary II
Property development
Regulations
Schools & colleges
Travel
Topic prevalence
0.10
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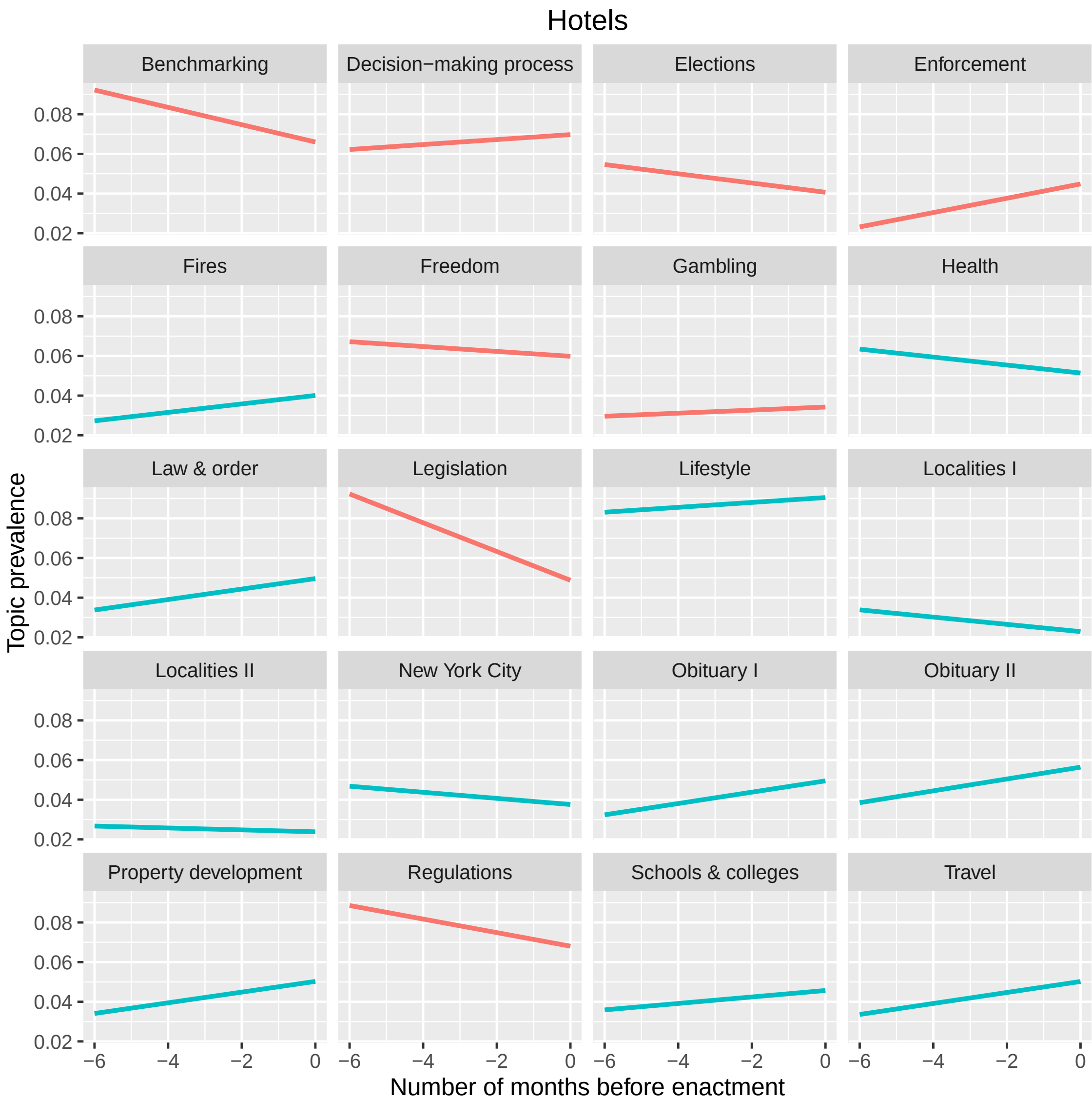
Number of months since enactment



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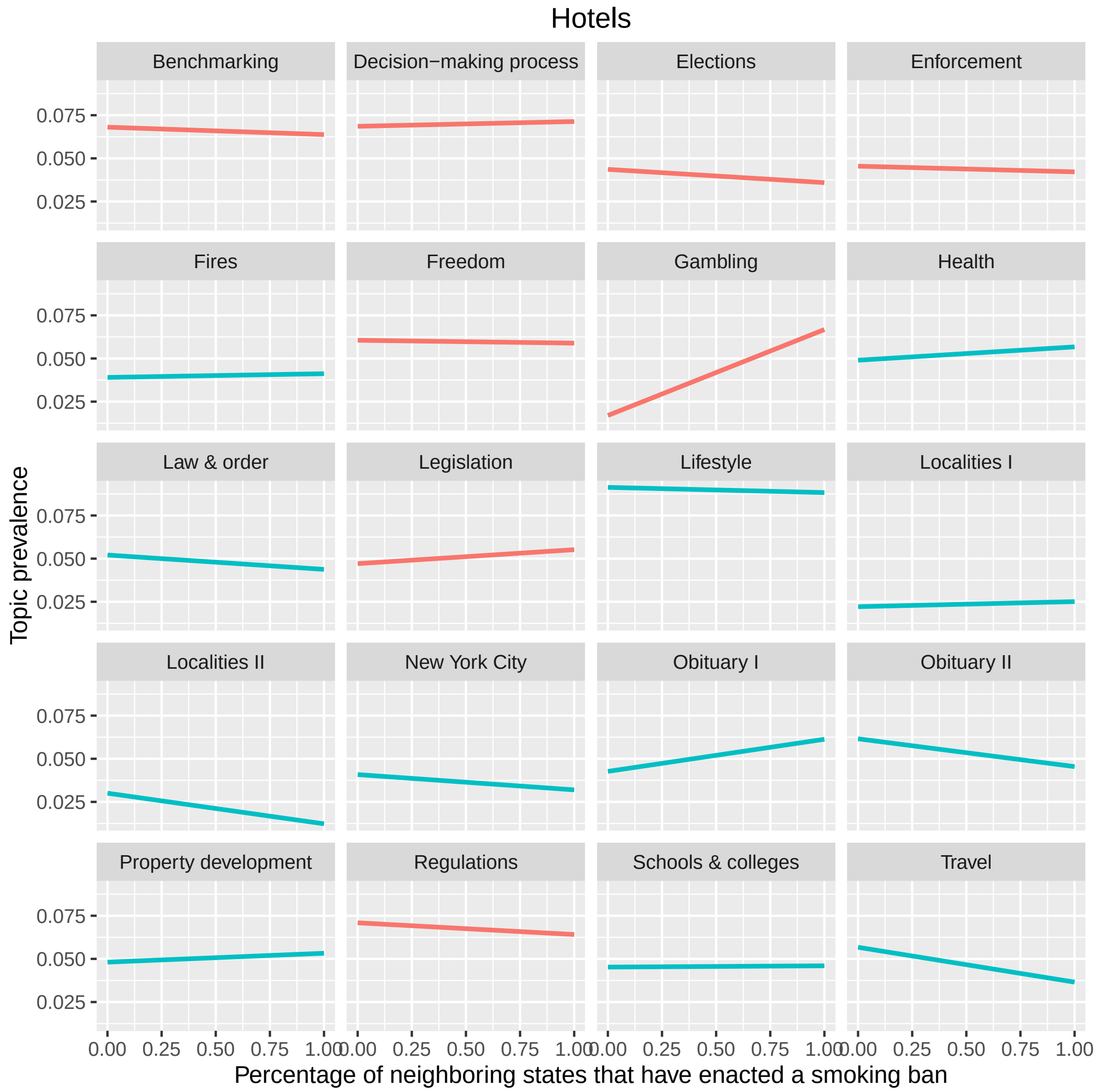
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Topic prevalence
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0.050
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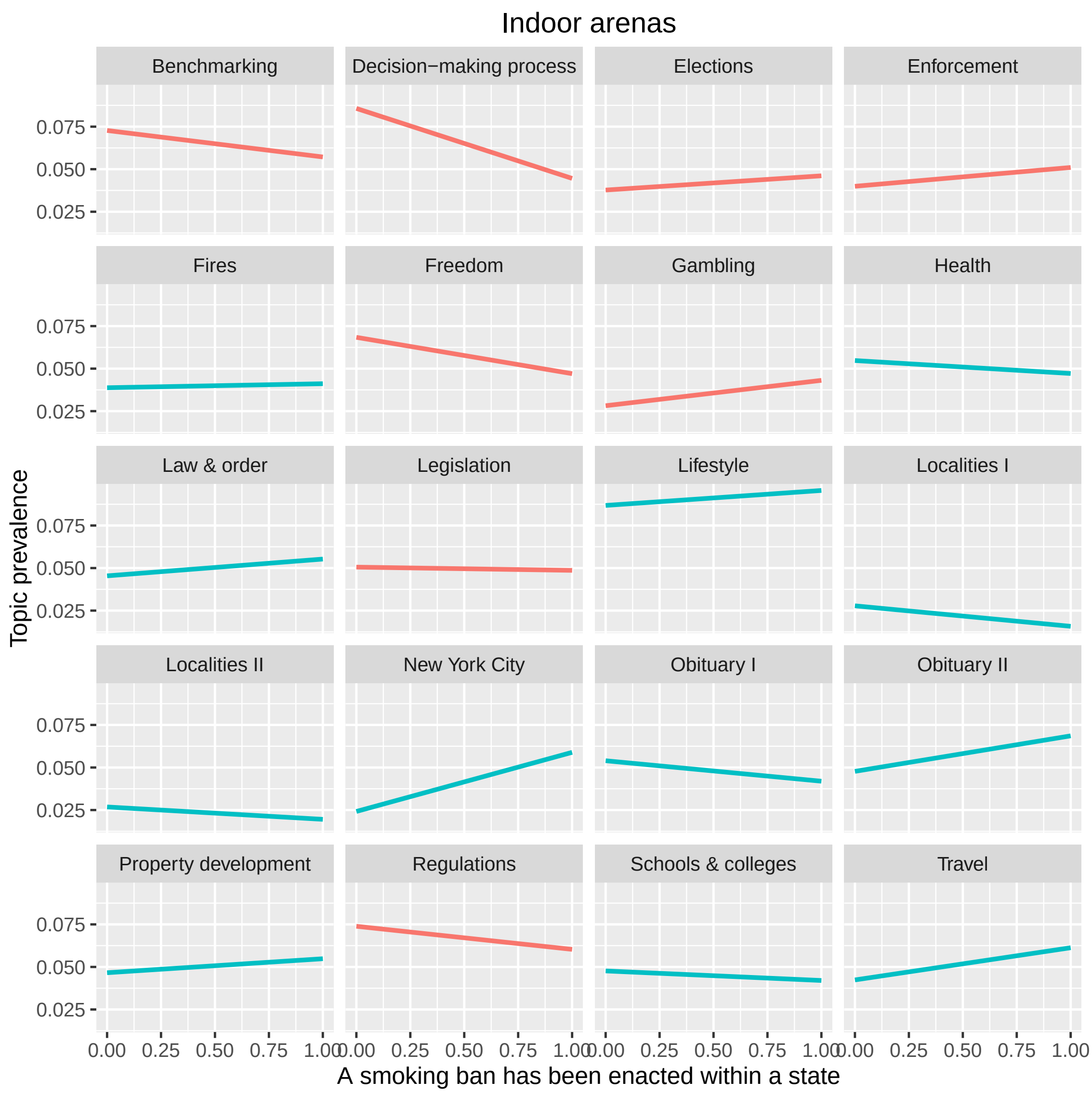
Percentage of neighboring states that have enacted a smoking ban


Indoor arenas
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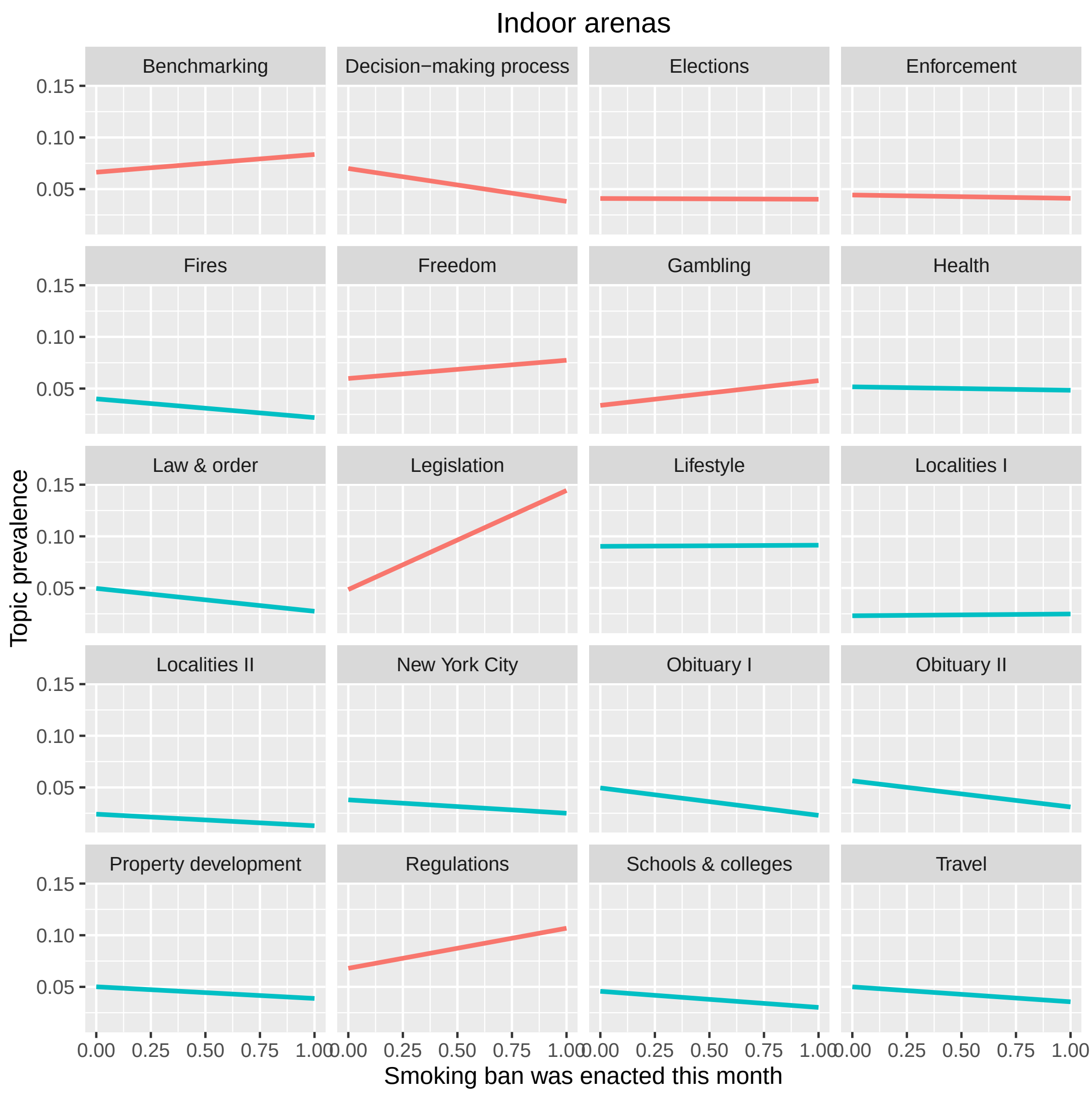
A smoking ban has been enacted within a state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Topic prevalence
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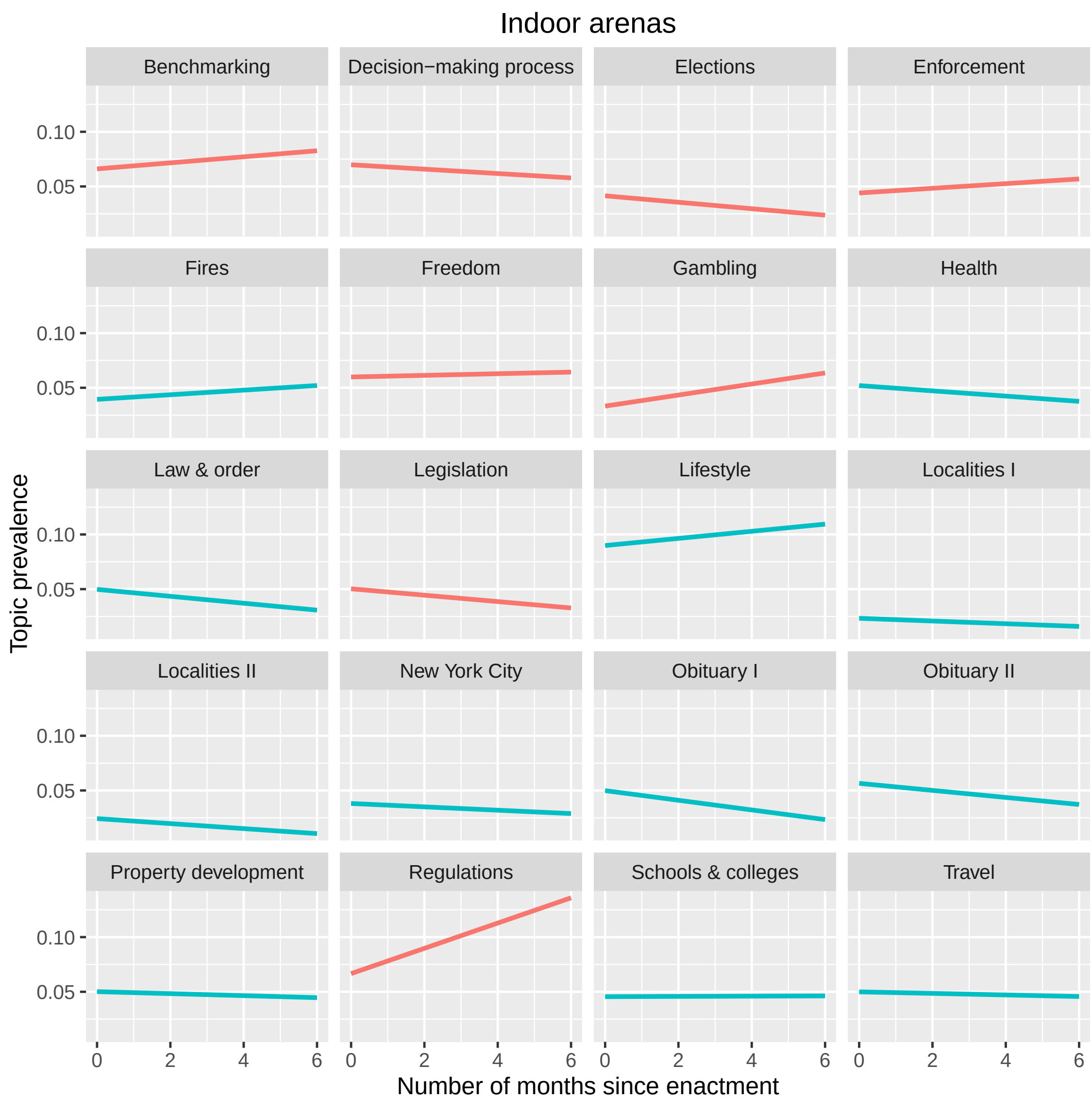
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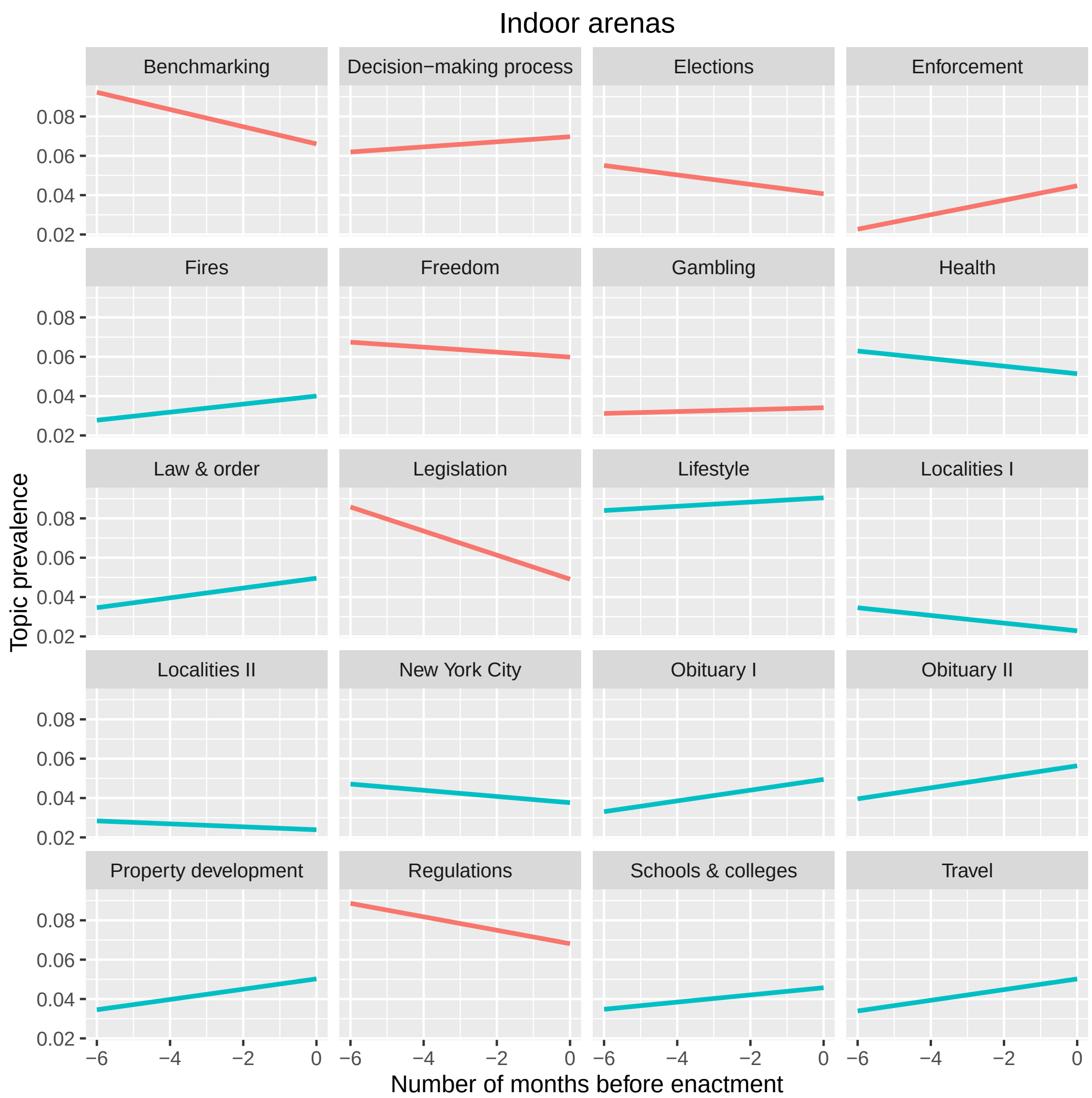
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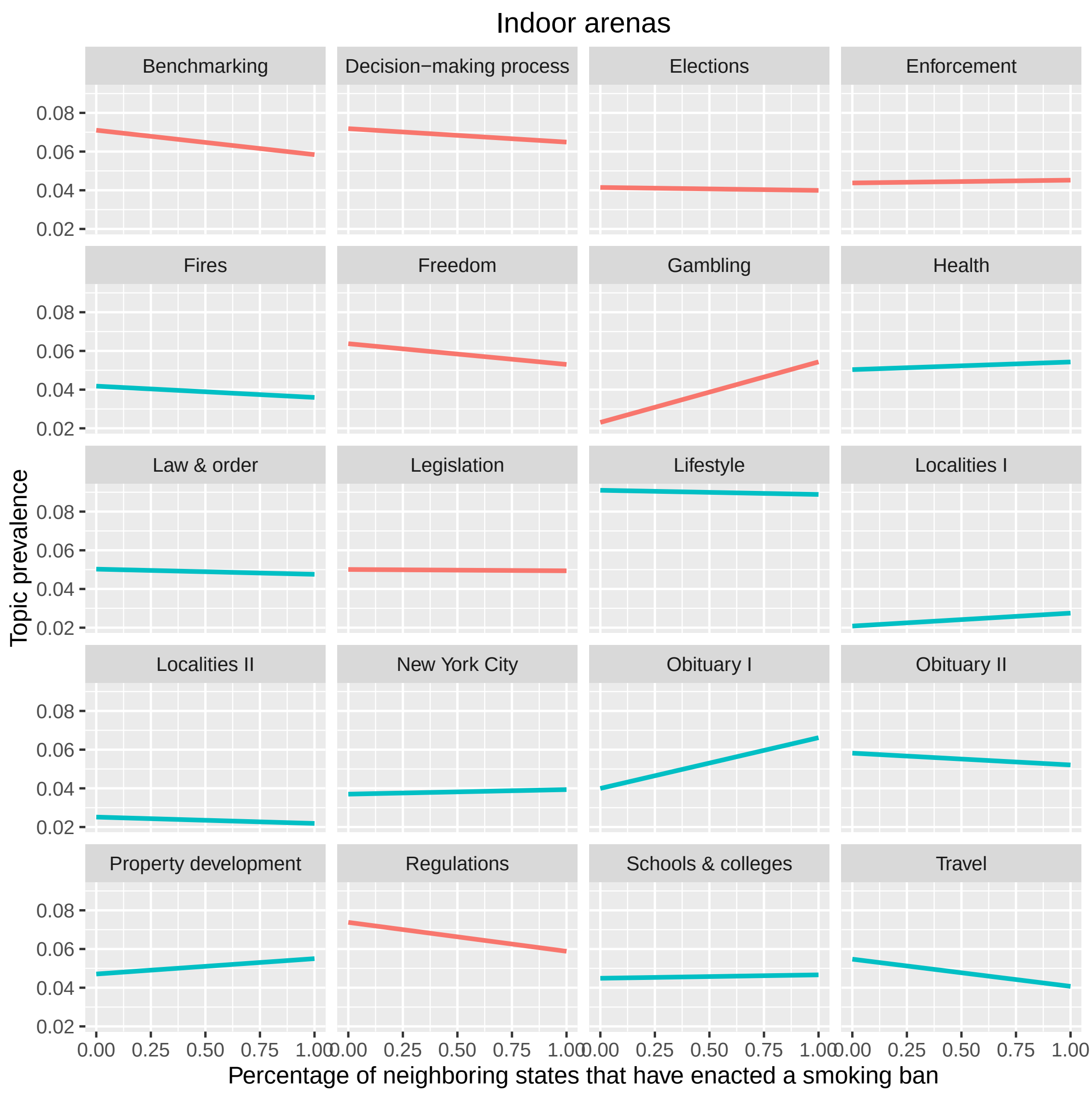
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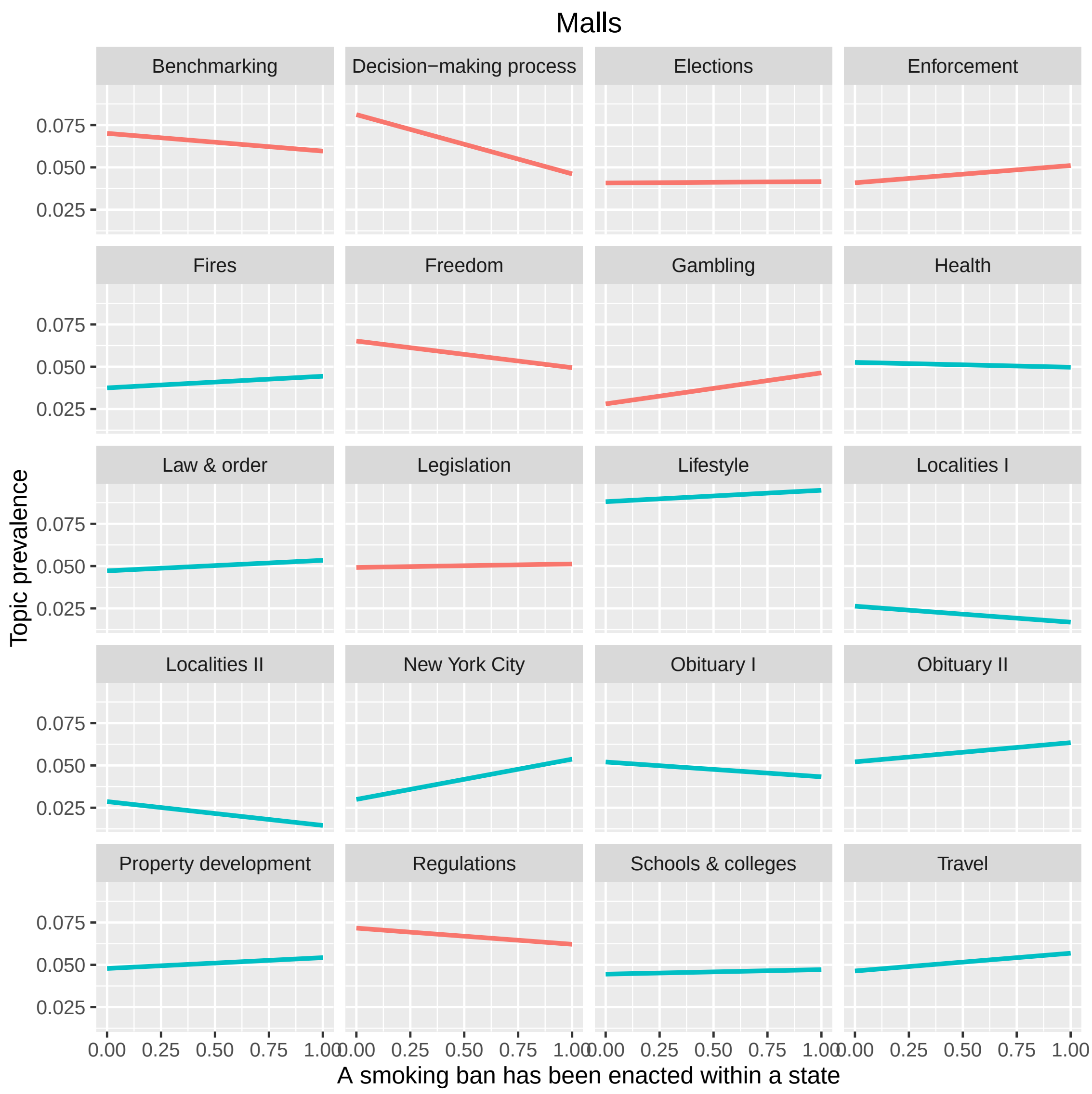
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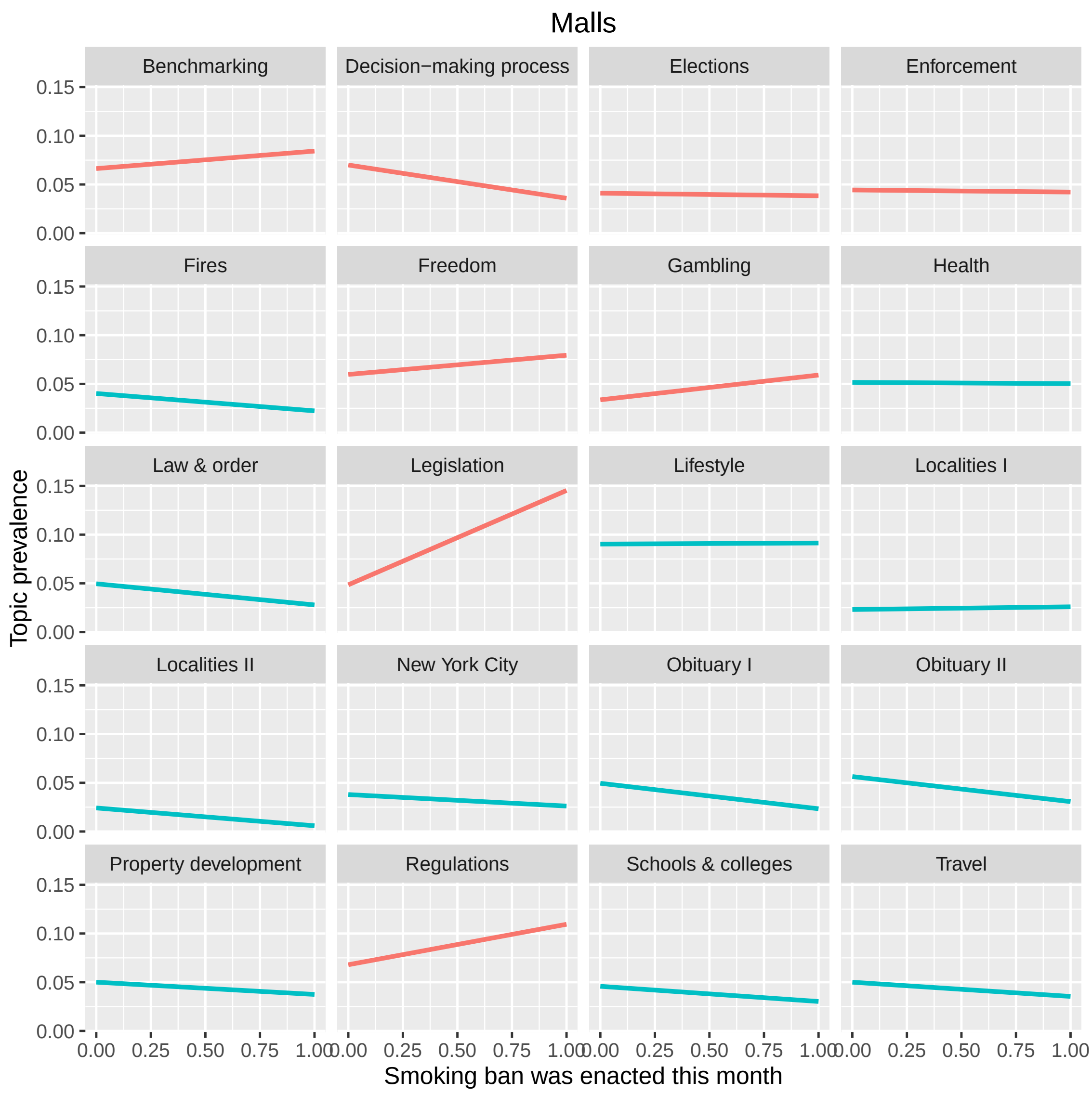
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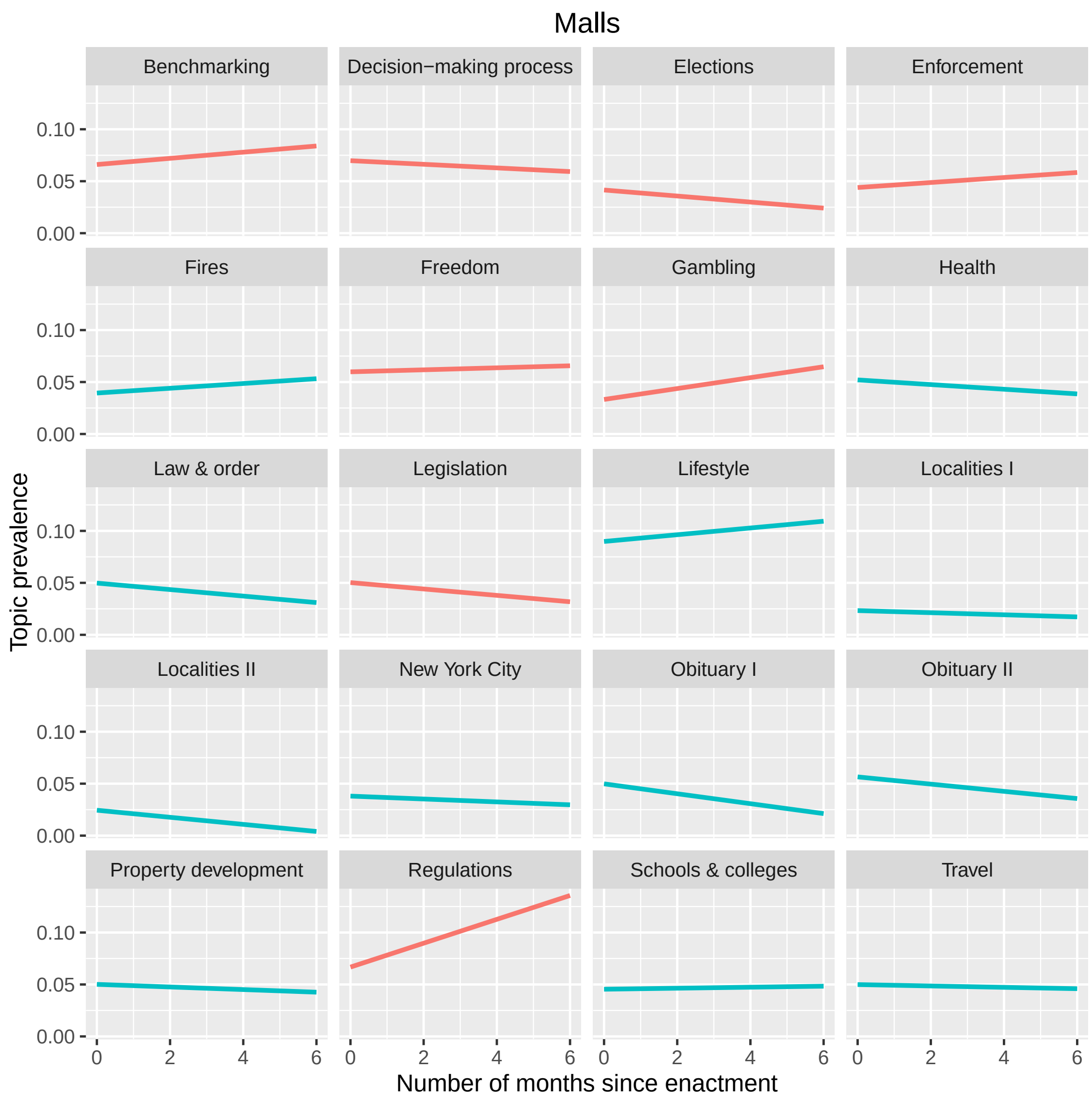

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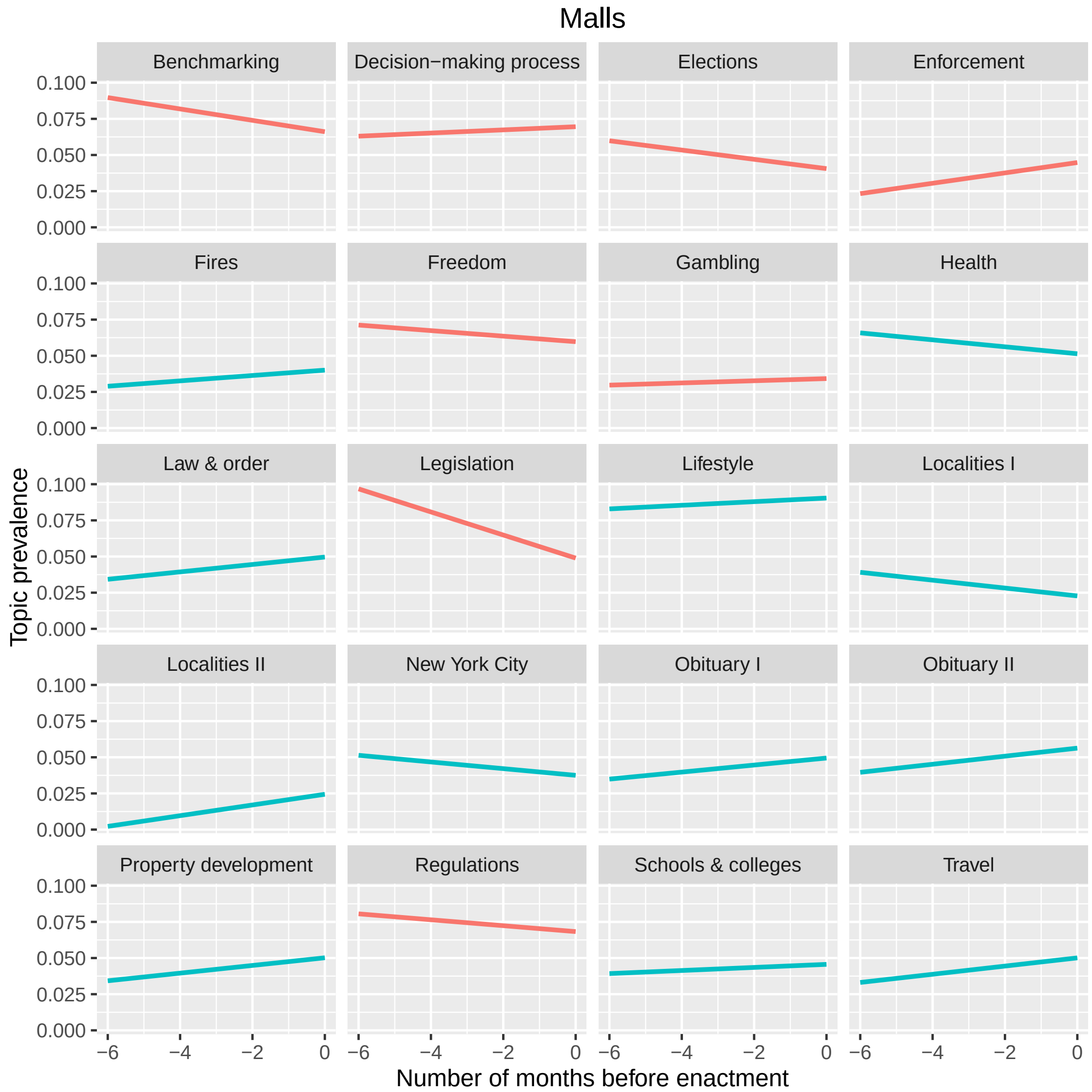

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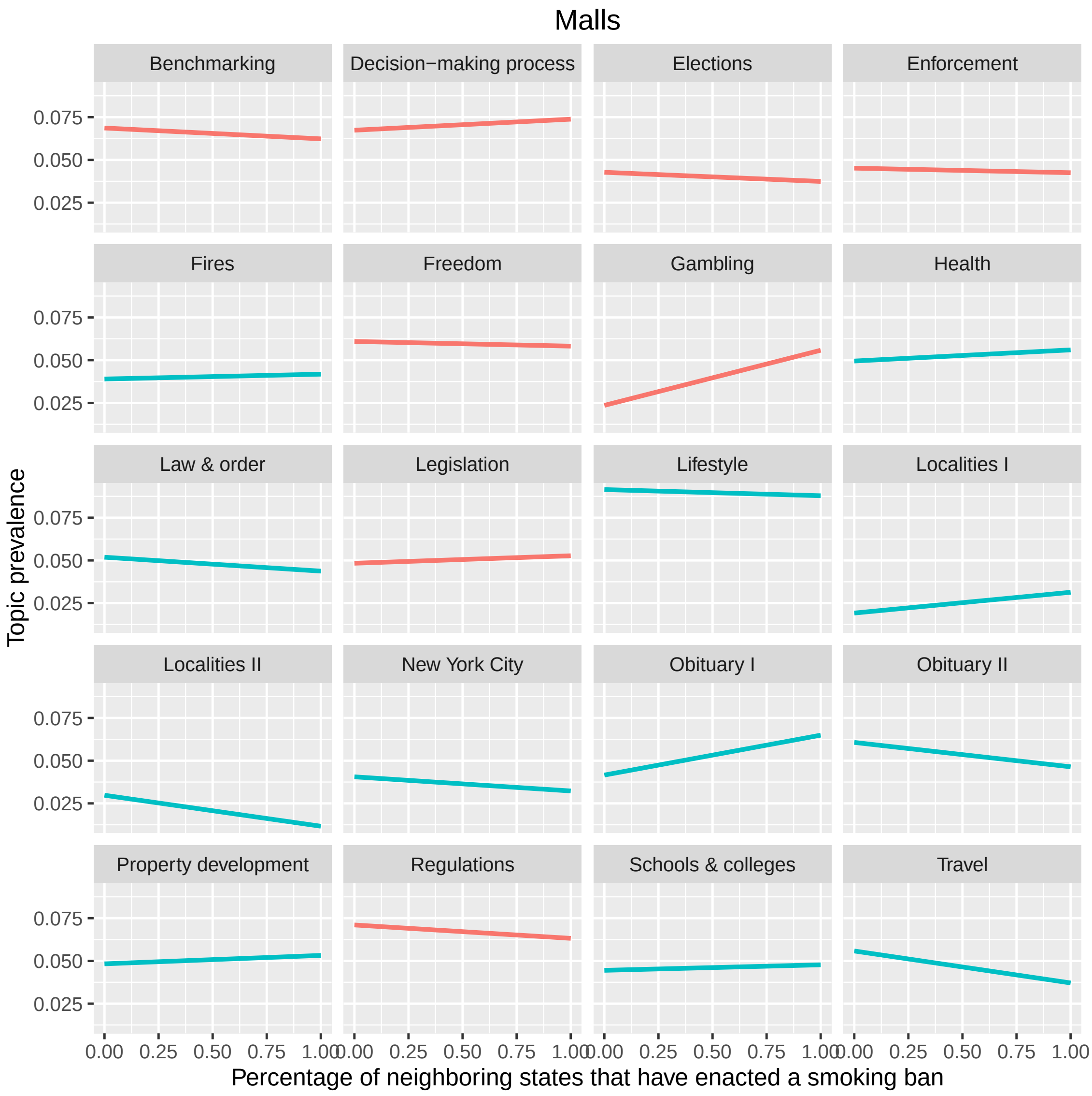

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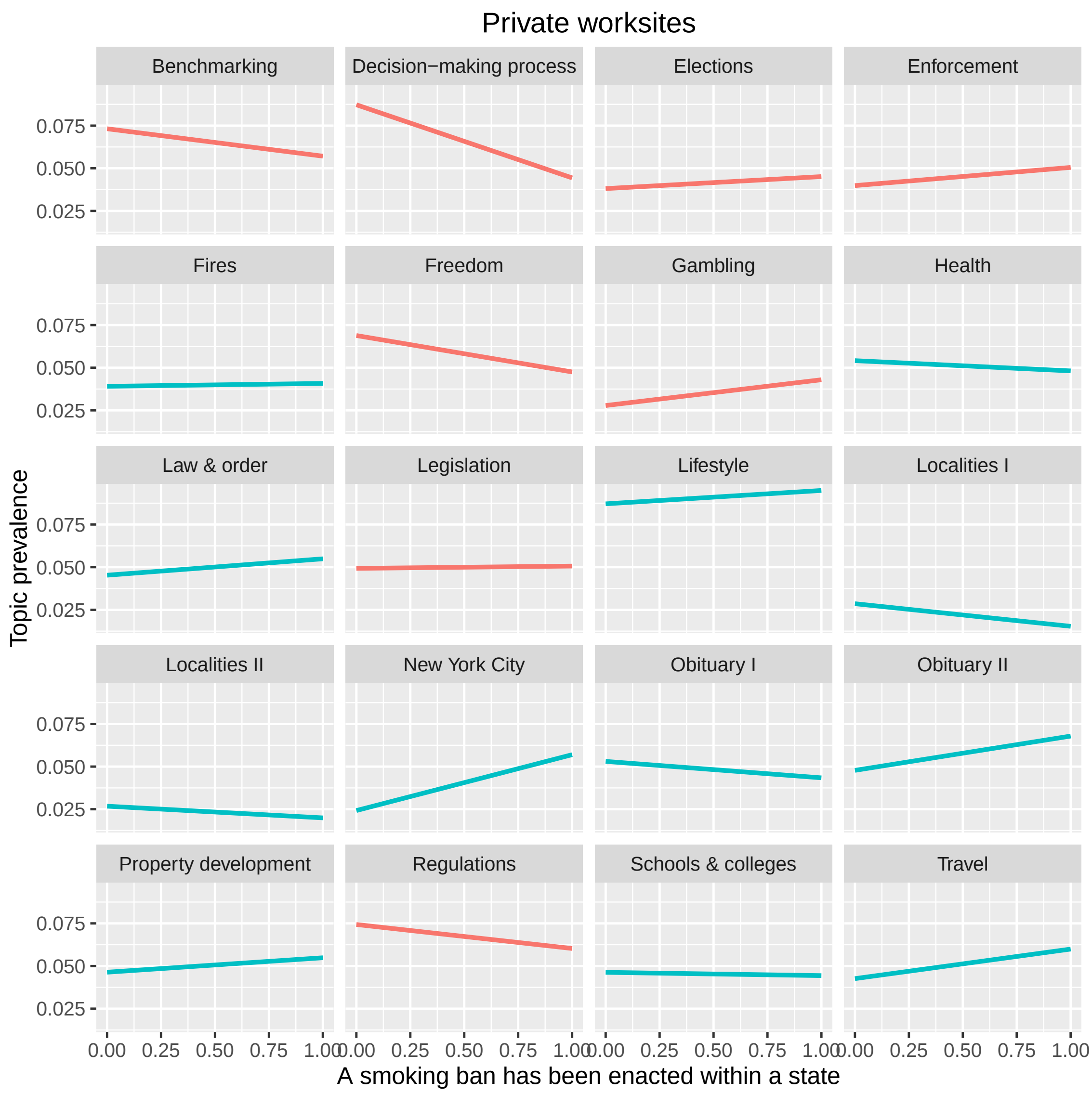
Private worksites
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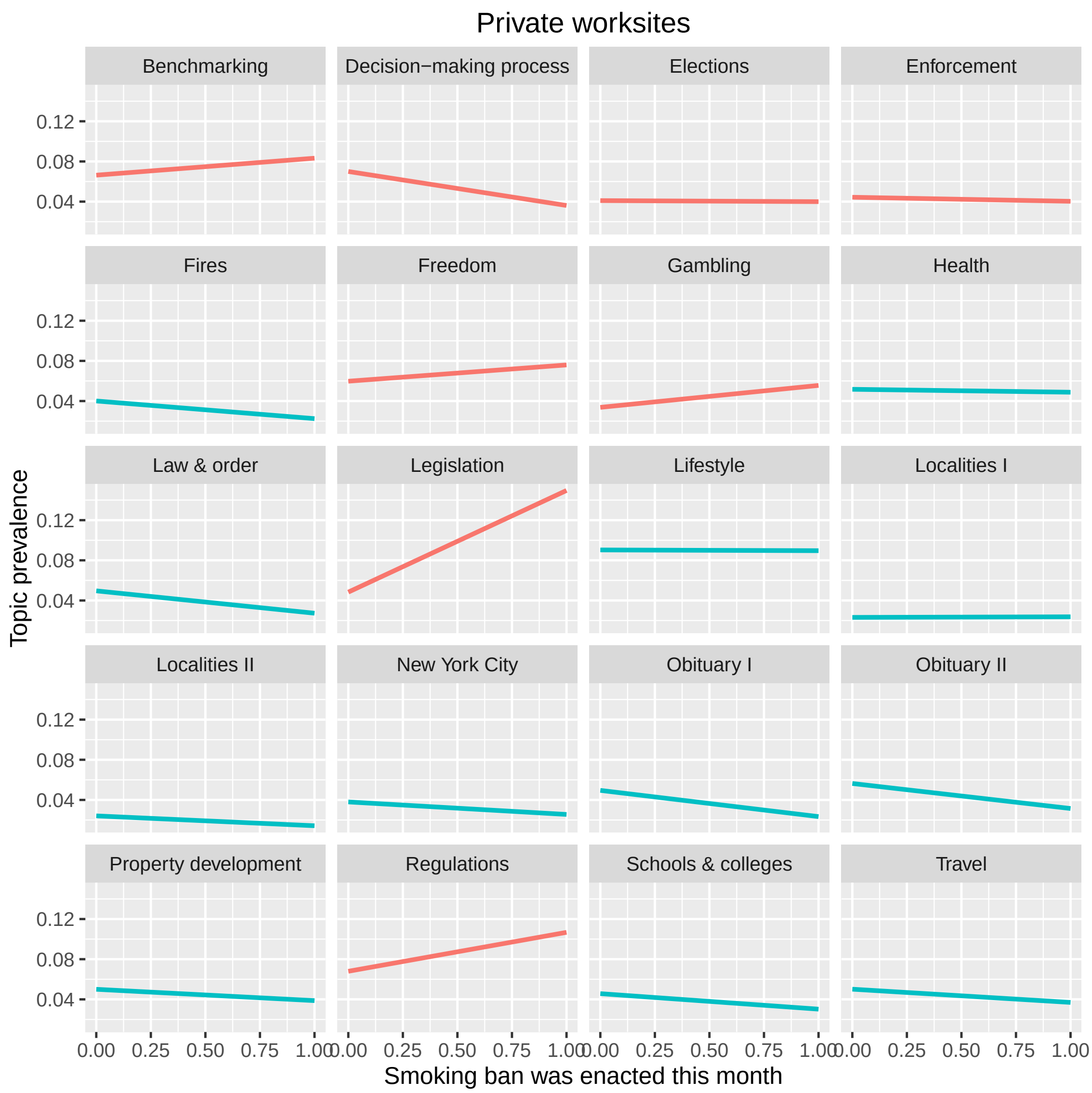

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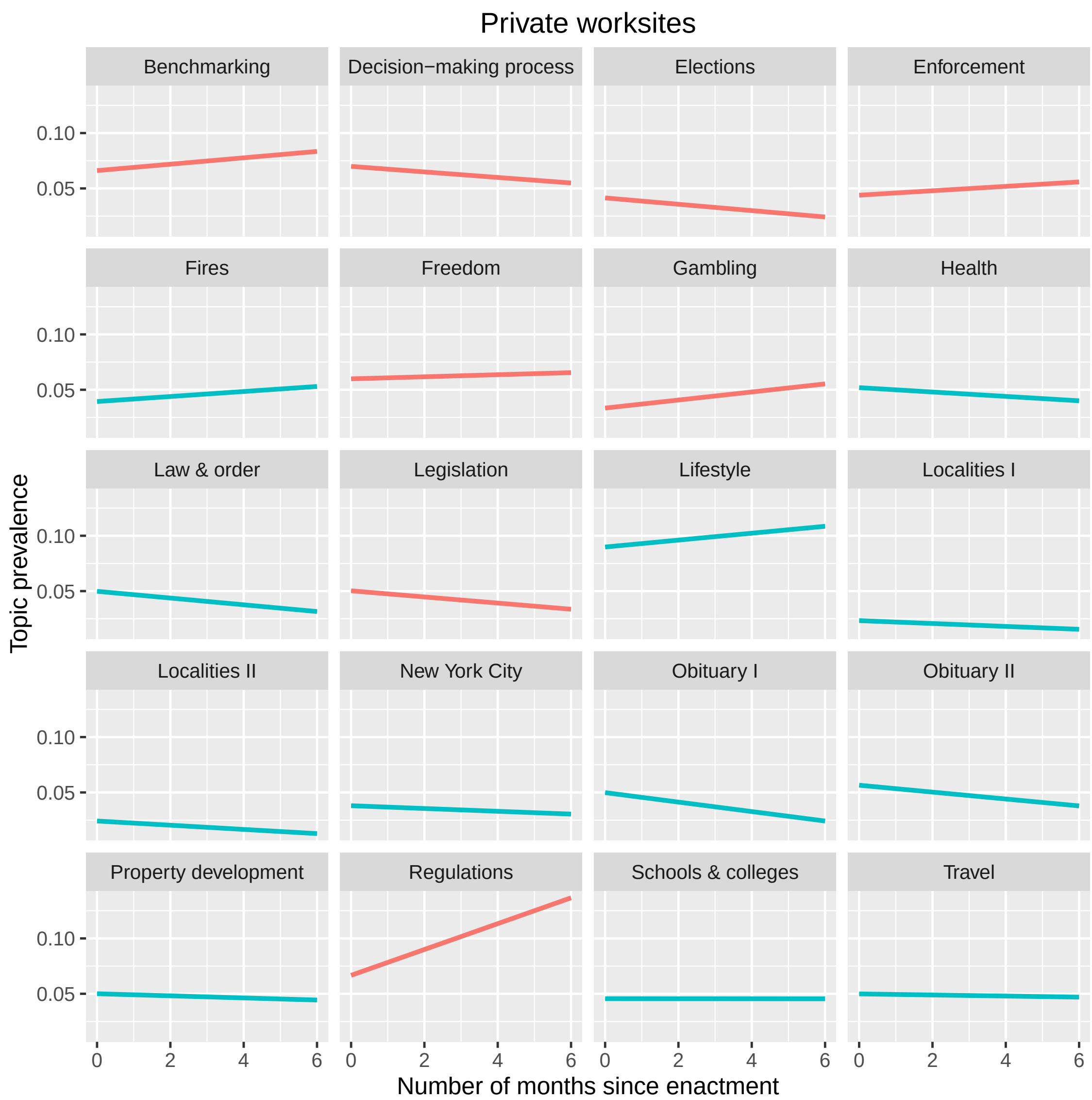

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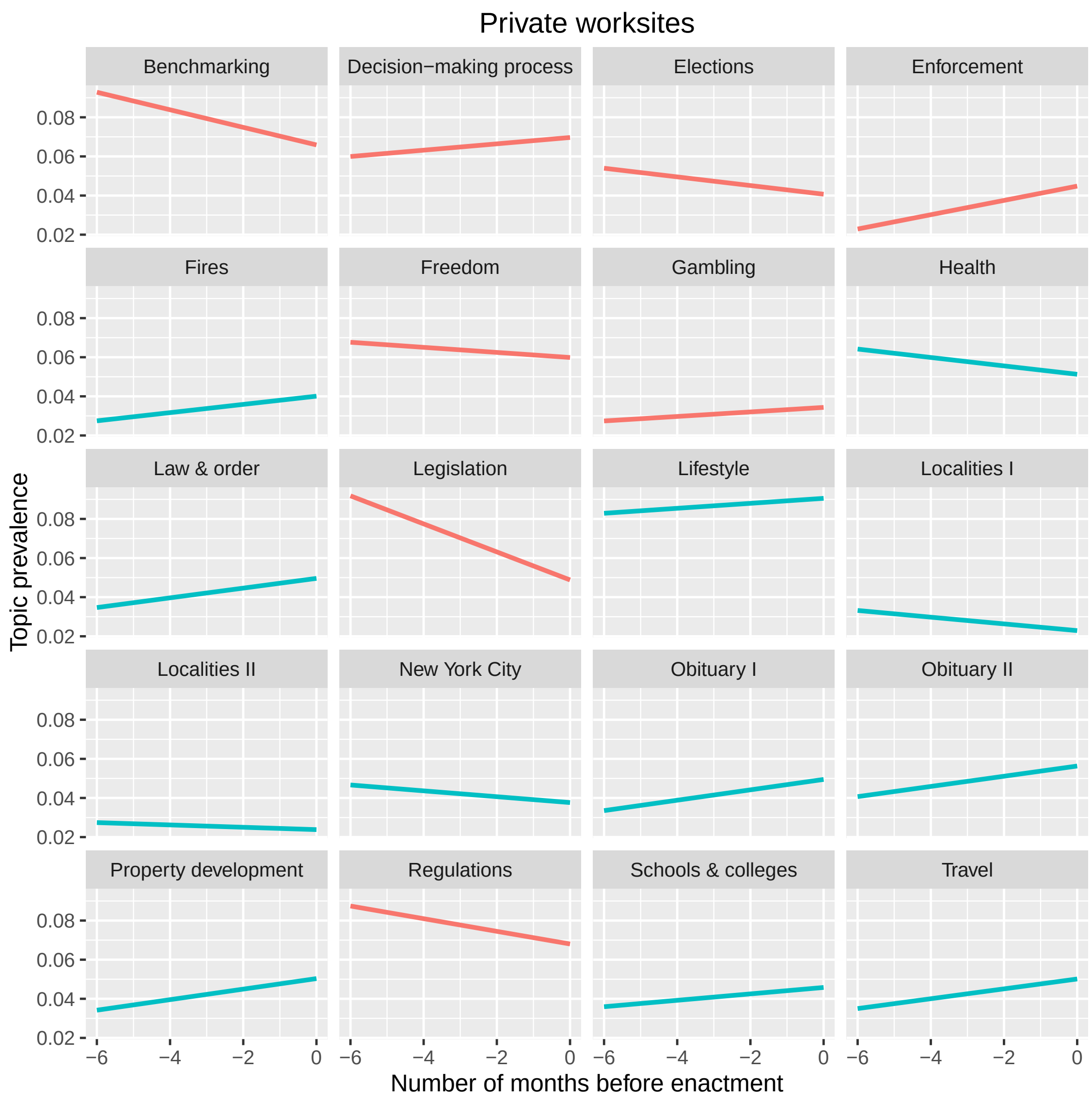

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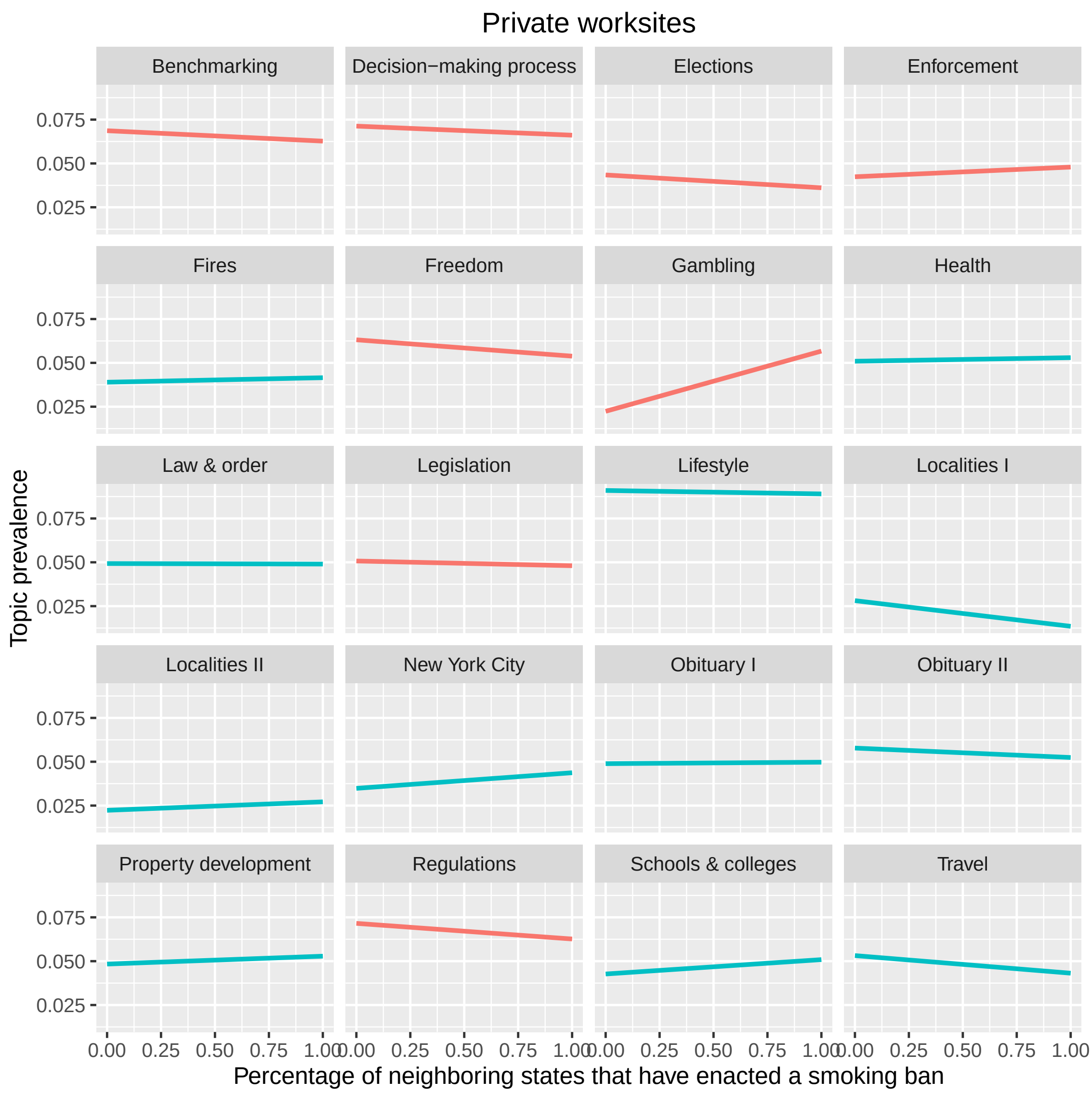
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