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Endogenous Jurisprudential Regimes

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Jurisprudential regime theory is a legal explanation of decision-making on the U.S. Supreme Court that asserts that a key precedent in an area of law fundamentally restructures the relationship between case characteristics and the outcomes of future cases. In this article, we offer a multivariate multiple change-point probit model that can be used to endogenously test for the existence of jurisprudential regimes. Unlike the previously employed methods, our model does so by estimating the locations of many possible change-points along with structural parameters. We estimate the model using Markov chain Monte Carlo methods, and use Bayesian model comparison to determine the number of change-points. Our findings are consistent with jurisprudential regimes in the Establishment Clause and administrative law contexts. We find little support for hypothesized regimes in the areas of free speech and search-and-seizure. The Bayesian multivariate change-point model we propose has broad potential applications to studying structural breaks in either regular or irregular time-series data about political institutions or processes.

1 Modeling Decision-Making on the U.S. Supreme Court

Supreme Court decisions do two things: they award a judgment, and they provide a rationale for that judgment in the form of a written opinion. The judgment of the case determines who wins and who loses in the legal dispute, and the terms of the victory or defeat. Opinions are important because they provide justifications for the judgment. Those who subscribe to the attitudinal model of judging (Segal and Spaeth 2002)—which asserts that the decisions the Justices reach are due solely to politics—argue that opinions are nothing more than disingenuous *post hoc* rationalizations of behavior that merely serve to cover up nothing more than unfettered politics.

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On the other hand, from a legal standpoint, it is hard to believe that opinions are inconsequential (Friedman 2006). To be sure, opinions are justifications, but they also provide legal rules that govern in future disputes. In our common law system, lower court judges rely on the collection of these rules—called precedents—when deciding subsequent cases. So, too, do litigants and potential litigants in society. It does not matter whether an opinion is persuasive or not in explaining how the Justices reached their decision in the particular dispute before the Court: what matters is that the opinion in the case creates a precedent that is used by others.

In order to adequately model decision-making on the Supreme Court, it is necessary to model both of these decisions. In other words, there are *two* dependent variables of interest: the judgment and the opinion. The vast majority of empirical scholarship that looks at the Supreme Court only considers the judgment. The reason is obvious: it is relatively easy to read a written opinion and code which party wins or loses, whether the Justice is in the majority or not, or code—with some minor complications—whether the Justice voted liberally or conservatively on a particular issue. It is far, far harder to take a long written opinion and systematically code the rule. Much of the modeling literature envisions these rules as points in some space, but empirically placing them there has proven elusive. A notable exception is Corley's (2008) study of the use of litigant briefs in Supreme Court opinions. There is some related empirical literature about modeling various legal choices, such as issues of standing (Pierce 1999; Staudt 2004) or the standard of review (Baldez, Epstein, and Martin 2006), but none of these studies sufficiently model the opinion-writing process.

In this article, we are interested in empirically modeling judgments. Just as the opinion could form the basis for a dependent variable, the "law" in an opinion also can serve as an independent variable in empirical studies of judicial behavior. This article looks at the empirical modeling of judgments, recognizing that even then it is necessary to control for the effects of the opinion-writing decision. When empirical studies ignore the interdependent choices between the judgment and the rationale, it becomes difficult to know whether the decisions are grounded in "law" or something else—be it judicial preferences, concerns about external pressures, or the like. Although the data might ultimately show that these things are unrelated—proving the attitudinalists correct—it is difficult to reach that conclusion without considering more general empirical models that incorporate both legal concerns and policy motivations (Friedman 2006).

There are a number of sophisticated theoretical models that can provide some guidance. First and foremost is the case-space model pioneered by Kornhauser (1992a, 1992b). In its simplest form, this model formalizes the relationship among rules, the facts of the case, and the disposition. Rules are partitions of the case space, and dispositions are determined by the relative location of the facts of the case and the preferences of the Justices with regard to the rule. The model has many applications, for example, the rules versus standards debate (Jacobi and Tiller 2007). See Lax (2011) for a comprehensive review of the refinements and application of this model, what he aptly calls "doctrinal politics." Carrubba et al. (2012) provide an alternative formal model of decision-making that incorporates trade-offs between reaching palatable dispositions and crafting useful rules. Clark and Lauderdale (2010) provide a novel empirical strategy to locate opinions in policy space, a potential building block for future studies.

Many empirical studies wholly ignore these interdependent choices. It is, thus, impossible to know whether judging is all about politics, all about law, or something else. There are some notable studies of judgments that take legal factors into account. Segal (1986) studies merit votes in search-and-seizure cases, and shows that a number of legal factors are indeed related to behavior, even when controlling for political ideology (see also Segal and Spaeth 2002). George and Epstein (1992) look at all Supreme Court death penalty cases from 1971 to 1988, and find that a model that integrates political factors and legal factors performs best. In both these studies, the legal factors discussed in the opinions were used to encode relevant legal factors. Using novel data culled from the Justices' papers, Maltzman, Spriggs, and Wahlbeck (2000) find evidence of the strategic relationship between opinion-writing and the ultimate disposition of cases.

Taken as a whole, these studies do provide support for the idea that dispositions of cases in the Supreme Court are influenced by factors related to opinion-writing. While these studies show that this may be descriptively the case, we are left wondering what mechanism is in place. When casting

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votes on the merits, how do Justices weigh the legal factors; that is, how important (or unimportant) is law?

2 Jurisprudential Regimes

In their path breaking study, Richards and Kritzer (2002) provide an answer to this question. They offer an alternative to previous approaches by arguing that "... the central role of law in Supreme Court decision making is not to be found in precedents that predict how justices will vote in future cases. Rather, law at the Supreme Court level is to be found in the structures the justices create to guide future decision making ..." (p. 306). In other words, it is not the factual circumstances of a prior precedent that matter so much as the doctrinal test setup that governs future cases. Richards and Kritzer offer the concept of a *jurisprudential regime*, which refers to "a key precedent, or a set of related precedents, that structures the way in which the Supreme Court justices evaluate key elements of cases in arriving at decisions in a particular legal area" (Richards and Kritzer 2002, 308). The basic idea is that after a key precedent, we would expect to see the patterns of decision-making to be different; certain key precedents create fundamentally different doctrinal tests, such that we might expect to see an important shift in outcomes thereafter. Ultimately, Kritzer and Richards argue that precedent itself can sometimes constrain Supreme Court Justices; to the extent that precedent constrains Supreme Court Justices, the constraint is found in these jurisprudential regimes.

The story is quite plausible. Consider the case of *Miranda v. Arizona*, 384 U.S. 436 (1966), which held that in cases of "custodial interrogation" it is necessary for the police to inform the individual being held that she has a right to remain silent, that anything she says can be used in court, that she has a right to an attorney, and that if she cannot afford an attorney one will be provided for her. After *Miranda* there is a whole line of cases that come before the Court about whether different types of questioning by police is "custodial interrogation"; for example, *Berkemer v. McCarty*, 468 U.S. 420 (1984), which held that roadside questioning during a traffic stop is not routine custodial interrogation. What the term "custodial interrogation" means becomes an issue after the *Miranda* decision. *Miranda* defined the jurisprudential regime by structuring the issues in future decisions.

The Richards and Kritzer jurisprudential regime studies share the same research design. Each study looks at a series of cases in a single area of law. The dependent variable in the study is the vote each Justice casts on the judgment. These outcomes are dichotomous, and are relatively easy to code since the cases fall in a single issue area. The next step is to code and collect the relevant covariates. To do so, it is necessary to read the cases and inductively develop a set of indicators that are likely to be related to the merit votes. In the free-speech domain, some of these factors include whether or not the speech is content based or content neutral, or whether the person speaking is a politician. This is precisely what Kritzer and Richards mean by a jurisprudential regime: that the factors that decide cases have shifted. These factors are coded for all cases, both before and after the regime change. Jurisprudential regimes can be conceptualized as structural breaks, so finding the key case (or set of cases) that have fundamentally changed the legal issue is important. To do this, Richards and Kritzer survey constitutional law texts and law reviews to find the case (or set of cases) that meets this criteria. They take the case(s) they identify from the exogenous sources as representing the structural break.

The empirical strategy is straightforward. In essence, Kritzer and Richards ask: does ideology (as measured by the scores of Segal and Cover 1989) predict the results, or can we establish that a doctrinal test does so? A dichotomous choice model is fit to the vote data. The ideology covariate and the collection of legal factors are included in the model. Each of these variables is interacted with an indicator that locates the structural break. A likelihood ratio test is then used to see whether the block of parameters after the change are different from those before. If the null of no difference is rejected, and if the parameters are substantively meaningfully different across regimes, then one can conclude that a jurisprudential regime exists. Richards, Kritzer, and their co-authors use this basic research design in a series of four articles. In these articles, they find support for jurisprudential regimes in four areas of law: freedom of expression (Richards and Kritzer 2002), the Establishment Clause (Kritzer and Richards 2003), search-and-seizure (Kritzer and Richards

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2005), and administrative law (Richards, Smith, and Kritzer 2006). We will return to each of these areas when we present our results.

There are some reasons to be very skeptical of these findings. First, the approach *assumes* that there is one—and only one—point in time where a jurisprudential change takes place. It also *assumes* that the location of the change is known with certainty, and that the structural break is immediate and sharp. This is problematic because there may be multiple regimes. Since many legal concepts are fuzzy and because several decisions may be necessary to sort out the interstices in existing precedent, transitions may not be quick. Second, it requires collecting the relevant covariates to capture the nature of the doctrine.[1] Finally, the likelihood ratio test that is used is falsely discriminatory (Lax and Rader 2010), and does not entertain the possibility of multiple breaks or breaks located elsewhere. In their reanalysis of these four studies using a randomization test, Lax and Rader (2010) find "only weak evidence that major Supreme Court precedents affect the way the justices themselves vote in subsequent cases" (p. 282).[2] Taking these studies as a whole, the evidence for the existence of jurisprudential regimes is shaky. But that evidence depends on the basic empirical strategy and its warts.

3 Endogenous Jurisprudential Regimes with a Probit Multiple Change-Point Model

Our purpose in this article is to provide an empirical model that endogenizes the empirical study of jurisprudential regimes. Ideally, the modeling strategy would be able to accomplish the following. First, it would not assume that a single change-point exists; it would allow the possibility of multiple change-points. Second, it would not require specifying *ex ante* the location of change-points. These two features would allow the *data* to speak about the existence, or not, and location of change-points. Our inferential strategy would also need to reflect uncertainty about the location of change-points, indicating whether or not the breaks are sharp or slow to evolve. The model needs to deal with the possibility of unidentified structural parameters, since some covariates may not vary within a regime. And, finally, our strategy needs to empower us to formally compare models that may or may not be nested, ideally on the scale of probability. The model we propose in this section meets these desiderata.

3.1 *Data and Research Design*

To empirically test the hypothesis that precedents affect Supreme Court decision-making and change "jurisprudential regimes," we use the same data sets in the Richards and Kritzer studies to detect structural breaks in the sample time period. We replicate and extend the studies in the four areas of law that have been studied using this approach.[3] The data are consistent with a jurisprudential regime if a regime shift is found, and if the structural parameters are substantively different across regimes. The methodology we apply in this article not only answers the change-or-no-change question, but is also able to address the following three important questions.

First, how many changes have occurred in the sample time period? The previous studies (Richards and Kritzer 2002; Kritzer and Richards 2003, 2005; Richards, Smith, and Kritzer 2006; Lax and Rader 2010) only consider the two possible scenarios of no change and one change, though it is possible that there are two or more regime changes. For instance, in the freedom of expression study, there are 4986 votes within 570 cases over 38 years. How can we be so sure that *Grayned v. Rockford*, 408 U.S. 104 (1972), is the only possible change-point? We should not rule out all the other cases. Suppose, for example, that the true regime evolution is *regime A* to *regime B* and back to *regime A*. If we mistakenly assume that there is only one change

[1] We do not address this limitation here. It does imply that these empirical models are, at best, descriptive. They nonetheless can determine the extent to which legal factors are related to decision-making while simultaneously controlling for ideology.

[2] As discussed below, the randomization test proposed by Lax and Rader (2010) is not powerful when the location of the change-point is incorrect.

[3] For replication data and code, see Pang et al. (2012).

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and locate the change-point in the middle of regime B, a statistical test will fail to reject the null that there is no regime change, but the fact is that there are, in fact, two change-points.

Second, when did the regime changes occur? Or in other words, what are the cases that caused regime change, if any? Locating the change-points is important for testing whether the difference of the "before" and "after" regimes are observed simply by chance. In the previous studies, the single change-point in each of the four areas is predetermined—*Grayned v. Rockford*, 408 U.S. 104 (1972) (in freedom of speech), *Lemon v. Kurtzman*, 403 U.S. 602 (1971) (in religious establishment), six cases dealing with issues as disparate as what constitutes probable cause and the application of the exclusionary rule (in search-and-seizure),[4] and *Chevron v. Natural Resources Defense Council*, 467 U.S. 837 (1984) (in administrative law). Although identifying those cases as change-points has some theoretical justification, it is not desirable to exclude all the other cases from consideration. Kritzer and Richards check robustness by using neighboring cases as alternative change-points. But most of the cases are still out of consideration. Furthermore, as Lax and Rader (2010) point out, this kind of robustness check is not convincing, because the neighboring observations are expected to produce similar testing results.

Third, how confident are we about the estimated number and location of the change-points? We always have uncertainty about any quantities inferred based on a finite sample. A regime may have subregimes, and a subregime can have its own subregimes. How fine the classification should be depends on the information contained in the observed data. To answer this question, we need to formally compare models with different numbers of change-points; these models will not be nested. We adopt a fully Bayesian modeling strategy, and use Bayes's factors for model comparison.

3.2 *A Multiple Change-Point Model*

The literature on using multiple change-point models to detect unknown change-points in time-series analysis is well developed in both the frequentist and Bayesian paradigms. For the frequentist approach, the most straightforward method is to adopt the principle of dynamic programming to conduct a grid search in order to minimize the loss function (most often the residual sum of squares) over all partitions of a time series given a predetermined number of change-points (Bai and Perron 2003; Qu and Perron 2007). The method quickly becomes computationally excessive when the number of change-points is greater than 2. An alternative frequentist approach is the binary segmentation procedure that tests recursively the presence of a change-point until no segments have any more change-points (Olshen and Venlatraman 2004). A variety of Penalized Maximum Likelihood estimators have also been used to estimate and test structural breaks, such as the penalized contrast estimator (Lavielle 2005), the minimum description length principle (Davis, Lee, and Rodriguez-Yam 2006), and many others (e.g., Siegmund 2004; Zhang and Siegmund 2007). There is a large Bayesian literature on multiple change-point models (e.g., Carlin, Gelfand, and Smith 1992; Barry and Hartigan 1993; Chib 1996, 1998; Hawkins 2001; Minin et al. 2005). The Bayesian methods for structural-break problems apply Markov chain Monte Carlo methods, which allow one to work with a rich set of models. In political science, Bayesian single (Spirling 2007) and multiple (Brandt and Sandler 2010; Park 2010, 2011) change-point models have been increasingly applied to detect structural breaks and improved model-fitting. In this article, we apply a Bayesian probit multiple change-point model for grouped time-series data. The model parameterization follows Chib (1998).

In a multiple change-point model, the process of regime evolution is modeled as a discrete-time discrete-state Markov process. If the process is in regime k at time t, then in the next time period $t+1$, there are two possibilities—it either stays in regime k (with probability $p_{k,k}$) or moves into regime $k+1$ (with probability $p_{k,k+1}$). By construction, $p_{k,k}+p_{k,k+1}=1$. This setup imposes a restriction that there is no jump over multiple regimes and that a reverse transition is not allowed.

[4]The cases are as follows: *Illinois v. Gates, 462 U.S. 213 (1983); Massachusetts v. Upton, 466 U.S. 727 (1984); Nix v. Williams, 467 U.S. 431 (1984); Segura v. U.S., 468 U.S. 796 (1984); United States v. Leon, 468 U.S. 897 (1984); and Massachusetts v. Sheppard, 468 U.S. 981 (1984).*

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This is a restrictive assumption. Nonetheless, the question under investigation is *whether* precedents change Supreme Court decision-making instead of *what direction* the change is. Therefore, since forward, backward, one-step, and multi-step transitions are all regime changes, this restriction does not affect the centerpiece of our hypothesis testing. Moreover, if the Court switched from a hypothetical regime A to regime B and back to regime A, the model would recover three regimes, with structural parameters the same, up to sampling error, in the first and third regimes.

Let s_t with $t = 1, 2, \ldots, T$ denote the discrete-time stochastic process of regime evolution, and $s_t = k \in \{1, 2, \ldots, K\}$, indicating that the process is in regime k at time t. Because it is a Markov process, we know that $\Pr(s_t|s_{t-1}, s_{t-2}, \ldots, s_1) = \Pr(s_t|s_{t-1})$. The conditional probability function of s_t can be built up as $\Pr(s_t = k|s_{t-1} = k) = p_{k,k}$ and $\Pr(s_t = k+1|s_{t-1} = k) = p_{k,k+1} = 1 - p_{k,k}$, given the assumption that either no change or one-step-forward transition is allowed in the process. In this setup, the change-points are easy to locate given a realization of the random vector $\mathbf{S} = \{s_1, \ldots, s_t, \ldots, s_T\}$. By definition, a change-point from regime k to regime $k+1$, τ_k, is at t if and only if $s_t = k$ and $s_{t+1} = k+1$. Two observations y_i and y_j belong to the same regime if and only if $s_i = s_j$, for all $i,j = 1, \ldots, T$. This model we propose directly estimates the latent discrete regime states $\mathbf{S}$ and locates all the change-points accordingly. Notice that in the setup the transition probabilities from s_{t-1} to s_t are not functions of the length of the interval $[t-1, t]$. The important implication of this property is that the observations do not have to be at equally spaced time intervals. In other words, the model can be applied to irregular time series with $t = 1, 2, \ldots, T$ as unequally spaced points in the time dimension. In this article, time is actually defined as the sequence of the cases. For instance, $t = j$ is the time when the jth decision is made. The number of months between two consecutive decisions may widely vary, but this irregularity does not incur any complications for us given our decision to focus on the sequence of decisions.

This multiple change-point model can also address the important issue of estimating K—the number of regime changes. In the Bayesian framework, there are two ways to estimate K. We can parametrize K in the model and estimate it at the same time with all other parameters. However, this approach requires reversible-jump MCMC (for RJMCMC, refer to Carlin and Chib 1995; Green 1995). RJMCMC involves changes of model dimensions and accordingly requires a dimension-matching condition through a user-chosen bijective function. This is difficult, and RJMCMC is rarely used other than in Poisson change-point models. Our approach is to use model comparison tools to choose the value of K. This approach treats the model itself as a random variable conditional on K, and then chooses the value of K based on the conditional model probability. That is, we estimate the random quantity $\Pr(\mathcal{M}|K, \mathbf{Y})$ with $K = 0, 1, \ldots, J$. The posterior of K is $\Pr(K|M, \mathbf{Y}) \propto \Pr(\mathcal{M}|K, \mathbf{Y})\Pr(K)$. With a discrete uniform prior of K, the posterior probability of the random variable K can be expressed as $\Pr(K = j|\mathcal{M}, \mathbf{Y}) = \Pr(\mathcal{M}|K = j, \mathbf{Y}) / \sum_{k=0}^{J} \Pr(\mathcal{M}|K = k, \mathbf{Y})$. That is, we can use model comparison with a different number of change-points to determine the value of K *ex post*.

This setup reflects the following hierarchical data-generating process: given K and P, the state variable ($\mathbf{S}$) is generated; given $\mathbf{S}$, the regime-specific structural coefficients are assigned; finally, the data are generated given the state-specific coefficients. The most important parameters for our purpose are the number of regime changes, K, and the locations of those changes $\Upsilon_K = \{\tau_1, \ldots, \tau_K\}$. These parameters tell us whether there is any structural break (whether $K = 0$), how many regime changes occurred ($K = ?$), and when the changes occurred ($\Upsilon_K = ?$).

3.3 *Model Specification*

Suppose $\mathbf{Y}_T = \{\mathbf{y}_1, \mathbf{y}_2, \ldots, \mathbf{y}_T\}$ is a multivariate time series, where $\mathbf{y}_t$ is an n_t-dimensional vector. In this article, t indicates the sequence of the decisions, $\mathbf{y}_t$ are the votes on the judgment, and n_t is the number of Justices at decision time t. The outcome variable $\mathbf{y}_t$ is a multivariate variable, because n_t is typically equal to nine, although because of recusal and turnover the number is sometimes smaller. This grouped time series is different from an ordinary time series because change-points will be between cases rather than between individual votes.

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The conditional distribution of $\mathbf{y}_t$ given the history $\mathbf{Y}_{t-1}=\{\mathbf{y}_1,\mathbf{y}_2,\ldots,\mathbf{y}_{t-1}\}$ depends on a parameter vector β_{s_t} that is specific to s_t the regime in time period t. Given the state variable $\mathbf{S}$, the probit multiple changing-point model can be specified as follows:

$$y_{i_t,t}=\mathbf{I}(z_{i_t,t}>0),\quad i_t=1,\ldots,n_t,\ \ t=1,\ldots,T \tag{1}$$

$$\mathbf{z}_t=\mathbf{x}_t'\beta_{s_t}+\xi_t, \tag{2}$$

$$\xi_t\sim N_{n_t}(\mathbf{0},\mathbf{I}). \tag{3}$$

This looks exactly like a regular probit model except that the coefficient β has a subscript s_t so that in equation (2) β_{s_t} is a regime-specific coefficient vector. If $y_{i_t,t}$ belongs to regime s_t, it is generated by the coefficient β_{s_t}. We call these parameters the structural parameters. Within a regime, these parameters need not be identified; if a covariate does not vary within a regime, the Bayesian model allows us to identify and update the corresponding coefficient via its prior so that we can maintain the same dimensionality of the parameter space for all regimes. This is one advantage of using a Bayesian inferential approach.

The Markov process s_t evolves following the rules set by the transition probability matrix:

$$P=\begin{pmatrix} p_{11} & p_{12} & 0 & \cdots & 0\\ 0 & p_{22} & p_{23} & \cdots & 0\\ \vdots & \vdots & \vdots & \vdots & \vdots\\ \cdots & \vdots & 0 & p_{KK} & p_{K,K+1}\\ 0 & 0 & \cdots & 0 & 1 \end{pmatrix}, \tag{4}$$

where $p_{ij}=\Pr(s_t=j|s_{t-1}=i)$ and $p_{ii}+p_{ij}=1(j-i=1 \text{ and } i,j\le K)$.

As with previous studies, we assume the observations are conditionally independent and the error terms have an identity covariance matrix within regimes. This is also a standard assumption made in change-point analysis. Lax and Rader (2010) point out that the violation of this assumption may affect the test result. Setting a change-point at the incorrect location would, by definition, cause dependence, which would affect the power of the test. Rather than assuming *ex ante* the location of the change-points, we allow the model to estimate them.

The possible correlation among observations can be handled in our model using a mixed-effect specification such as $z_{i_t,t}=\mathbf{x}_{i_t,t}'\beta_{s_t}+b_t+b_p+\xi_{i_t,t}$, where b_t is the decision-time-specific effect and b_p the Justice-specific effect. We choose not to use a mixed-effect specification, because with b_t included, we have the problem of too many small groups. Using the freedom-of-speech context as an example, there are 570 cases, and the number of votes within a case varies from 6 to 9. This means that we can at most use nine observations to estimate each b_t, and there are 570 such b_t's to estimate. Unless our variable selection has a serious omitted-variable problem, we will not get much Bayesian updating about the random-effect parameters. Estimating the b_p's would be equally problematic since we include ideology—a Justice-specific covariate—in the model.

The joint posterior based on the multiple change-point model can be expressed as follows:

$$f(\beta,\mathbf{S},P|\mathbf{Y})\propto\left(\prod_{s_t=1}^{K+1}f(\mathbf{Y}_{\in s_t}|\beta_{s_t})\pi(\beta_{s_t})\right)p(\mathbf{S}|P)\pi(P). \tag{5}$$

We use the prior distribution, $p_{ii}\sim$ Beta(1,1), that is equivalent to a uniform distribution. We choose this prior because we have little information about the transition probabilities, and are not capable of assigning defensible subjective priors. For the coefficients β_{s_t}, we use the same prior distribution for all regimes, $\mathrm{N}(\bar{\beta}_0,\mathbf{B}_0)$, where $\bar{\beta}_0=\mathbf{0}$ and $\mathbf{B}_0=100\times\mathbf{I}$. To estimate the model, we apply and modify the algorithm developed in Chib (1998) to deal with our grouped time series. The detailed Markov chain Monte Carlo algorithm for estimating a general clustered multiple change-point model is available in the supplementary materials. The posterior draws give us all the necessary information about the probability of regime change at each time period, and how different the regimes are is reflected by the regime-specific structural parameters.

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3.4 *Determining K: Bayesian Model Comparison*

We are uncertain about the number of change-points K in each of our applications. Rather than estimating it directly, we use tools of Bayesian model comparison to do the job (Kass and Raftery 1995). This approach works as follows. For each model, we keep all aspects the same, including the choice of covariates and the priors used in each regime. The only thing we allow to change is the number of change-points. We start the simplest model where $K=0$; that is, a simple probit model with no structural breaks. We then increase the value of K by one each time and compare the model quality with that of the previous models until we find that an increase in the number of change-points causes a decrease in model quality.

To compare the models with different numbers of change-points, we use the Bayes's factor. Suppose that the observed data $\mathbf{Y}$ could have been generated under one of two models: $\mathcal{M}_1$ and $\mathcal{M}_2$. A natural thing to ask from the Bayesian perspective is: what is the posterior probability that $\mathcal{M}_1$ is true (assuming either $\mathcal{M}_1$ or $\mathcal{M}_2$ is true)? Using Bayes's theorem, we have

$$\Pr(\mathcal{M}_k|\mathbf{Y}) = \frac{p(\mathbf{Y}|\mathcal{M}_k)\Pr(\mathcal{M}_k)}{p(\mathbf{Y}|\mathcal{M}_1)\Pr(\mathcal{M}_1) + p(\mathbf{Y}|\mathcal{M}_2)\Pr(\mathcal{M}_2)}, k = 1, 2. \tag{6}$$

To compare the two models, we can directly compare the posterior probabilities of the *models*:

$$\frac{\Pr(\mathcal{M}_1|\mathbf{Y})}{\Pr(\mathcal{M}_2|\mathbf{Y})} = \frac{p(\mathbf{Y}|\mathcal{M}_1)}{p(\mathbf{Y}|\mathcal{M}_2)} \times \frac{\Pr(\mathcal{M}_1)}{\Pr(\mathcal{M}_2)}. \tag{7}$$

The larger the posterior odds, the more the data are in favor of one model (say, $\mathcal{M}_1$). We usually assign a uniform model prior, then, the prior odds $\frac{\Pr(\mathcal{M}_1)}{\Pr(\mathcal{M}_2)}$ is 1 and model comparison only depends on the first term on the right-handside, which is called the Bayes's factor:

$$B_{12} = \frac{p(\mathbf{Y}|\mathcal{M}_1)}{p(\mathbf{Y}|\mathcal{M}_2)} \text{ and } \log B_{12} = \log p(\mathbf{Y}|\mathcal{M}_1) - \log p(\mathbf{Y}|\mathcal{M}_2). \tag{8}$$

When considering the Bayes's factor on logarithmic scales, a positive (negative) log Bayes's factor favors $\mathcal{M}_1(\mathcal{M}_2)$, and the greater the absolute value of a log Bayes's factor, the stronger evidence that one model is better than the other. Calculating the (log) Bayes's factor requires the marginal likelihoods of competing models. The marginal likelihood is defined as

$$p(\mathbf{Y}|\mathcal{M}_k) = \int_{\Theta_k} p(\mathbf{y}|\theta_k, \mathcal{M}_k)p(\theta_k|\mathcal{M}_k)d\theta_k. \tag{9}$$

To handle this high-dimensional integration problem, we use the estimation method proposed by Chib (1995) to approximate the marginal likelihood. The detailed MCMC scheme for estimating the marginal likelihood is included in the supplementary materials. For each model, we compute the marginal likelihood, and ultimately choose the model with the highest marginal likelihood. In other words, the best model is such that the log Bayes's factors of other competing models versus this model are all negative.[5]

4 Results

In this section, we report our findings from the four areas of law previously studied by Richards, Kritzer, and their co-authors. We take an identical strategy for each application. To facilitate comparison, we take as given the set of covariates from each of the studies. We then fit a probit model to the data ($K=0$), a deterministic change-point model where the change-point is set at the location used in the original study ($K=1$, and the model is labeled as $M_{1'}$ in the tables below), and

[5]Suppose that the true data-generating process has $K=6$. This approach would never find the true model if model performance began to degrade after $K=2$. We suspect this is not an issue with our data since our model began to recover redundant states. A redundant state refers to a state i that lasts for only a very few time periods and has a high transition probability p_{ij} in all the time periods. Nonetheless, it is a limitation of this strategy.

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Table 1 Log-marginal likelihoods and Bayes's factors for the freedom-of-expression results

Model	*Number of changing points*	*Marginal likelihood (ln)*	*Bayes's factor* ($log_{10}B_{M,M_4}$)
M_0	0 (Pooled Probit)	−3069.149	−25.306
$M_{1'}$	1 (Deterministic)	−3281.109	−117.360
M_1	1 (Probabilistic)	−3069.627	−25.513
M_2	2 (Probabilistic)	−3072.921	−26.944
M_3	3 (Probabilistic)	−3048.649	−16.399
M_4	4 (Probabilistic)	−3010.880	−.−
M_5	5 (Probabilistic)	−3028.911	−7.831
M_6	6 (Probabilistic)	−3031.344	−8.887

Note. In the log Bayes's factor, the marginal likelihood of M_4 is in the denominator, and a negative log-BF means that M_4 is favored by the data. The results are from a multivariate multiple change-point probit model. $N = 4986$

then a series of models where the change-points are probabilistically estimated starting at $K = 1$ and increasing the value of K and reestimating the model until the performance degrades. For each, we compute the marginal likelihoods. Since all the models are of the same data $\mathbf{Y}$, all can be compared using Bayes's factors.[6] We report the log-marginal likelihoods of all models and the log Bayes's factors of the competing models versus the best model we detect. For the best-performing model, we graphically report the location(s) of the change-point, and the structural parameters within each regime.[7]

4.1 *Freedom of Expression*

The first study that invoked the notion of jurisprudential regimes is Richards and Kritzer (2002). This study looks at the Supreme Court's freedom-of-expression cases from 1954 to 1998. These cases are based on the free-speech provisions of the First Amendment. The Court has long recognized that freedom of speech is not an absolute right. Based on their reading of the freedom-of-expression law, Richards and Kritzer (2002) suggest that two 1972 cases (*Chicago Police Department v. Mosley*, 408 U.S. 92 (1972), and *Grayned v. City of Rockford*, 408 U.S. 104, (1972)) established the speech-protective content-neutrality regime. In this regime, the identity of the speaker and the nature of the regulation are things judges should consider when determining whether or not a regulation of speech should be upheld as constitutional. The dependent variable is coded 1 (conservative) if the Justice votes to uphold the regulation and 0 (liberal) otherwise.

Table 1 contains the log-marginal likelihoods and Bayes's factors for the freedom-of-expression cases. In relative terms, models with a larger log-marginal likelihood are better. Interestingly, if we just compared the pooled probit model with the deterministic probit model, the pooled probit model is better! This suggests that the findings from the likelihood-ratio test are unreliable. The best model M_4 resoundingly beats the competitors. The posterior probability that it is the best model of the set exceeds 99%; Kass and Raftery (1995) would call this "Decisive" support for M_4. This model has four change-points; that is, five regimes where there are substantial differences in structural parameters.

Figure 1 contains the time-series plots of the locations of the regimes. The upper panel is a plot of the posterior probability of what regime the process is in at each time t, which is estimated by the frequency that s_t takes the value of $k = 1, 2, 3, 4$, or 5. The five lines from the darkest to the lightest

[6]In the search-and-seizure cases, we did not compare the deterministic change-point model conducted in Kritzer and Richards (2005), because their reported model omitted the 203 votes from Gates through Segura. Bayesian model comparison cannot be applied to models with different data.

[7]For each model reported, for both posterior simulation and the reduced MCMC runs for computing log-marginal likelihoods, we carried out simulations for 100,000 iterations after 10,000 discarded burn-in iterations. We used multiple graphical and empirical diagnostics to ensure that the simulations have converged.

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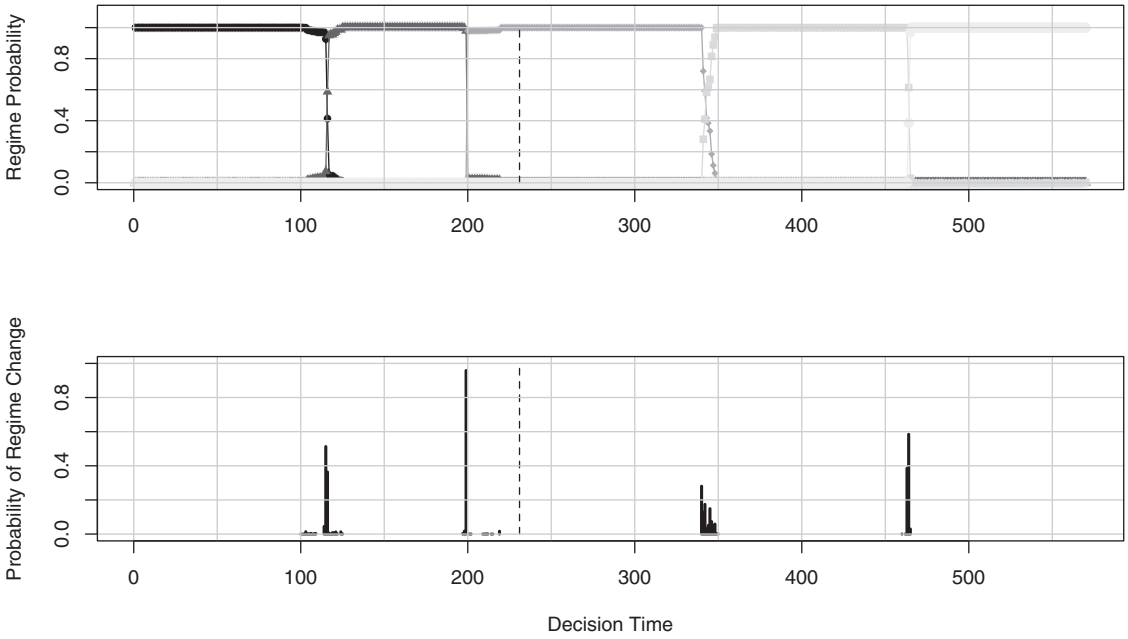


Fig. 1 Regime change and probabilities of regime-change time-series plots for freedom-of-expression model M_4. The vertical dashed line denotes *Grayned*.

one indicate the five regimes, respectively. The lower panel shows the transition probability at each time of decision. The two plots together summarize the posterior information about the stochastic process s_t. For example, Fig. 1 tells us that the cases between decision times 1 and 100 (the first 100 cases in the sequence) are in regime one with probability one, and their transition probabilities are all zero. The first regime transition occurs between times 101 (the 101st case) and 125 (the 125th case), while the black line (regime one) goes down from 1 to 0 and the dark-gray line (regime two) goes up from 0 to 1. The lower panel also shows that in this transition period the transition probability becomes non-zero and then is back to zero after the transition is complete. Decision time 115 (the 115th case) is the most likely change-point from regime one to regime two, with probability .513, indicated by the first spike in the lower panel.

In Table 2, we report the names and actual dates of the cases of the four regime transitions in these data, and all the reported cases are with probability no less than .001. Do these make substantive sense? Not really. The model misses the *Grayned* transition in 1972. The transition from Regime I to Regime II is close to the *New York Times v. Sullivan*, 376 U.S. 254 (1964), decision that changed libel law. The transition from Regime II to III is close to the important *Brandenburg v. Ohio*, 395 U.S. 444 (1969), case—where the Court held that the government cannot regulate speech unless it is likely to avoid "imminent lawless action"—and the *Schacht v. United States*, 398 U.S. 58 (1970), decision—holding that the use of an American military uniform as part of a theatrical production was protected, and that the content-based regulation based on whether or not the portrayal discredited the armed forces was unconstitutional. The model tells us that the case with the highest posterior probability of being a change-point is the *Jones* case that was a *per curiam* opinion dismissing *certiorari* as improvidently being granted in a case involving a university student suspended for distributing antiwar materials. Taken as a whole, it is impossible to tell a coherent story about how these findings square with our understanding of free-speech law.

For the sake of completeness, we report the structural parameters for the free-speech data in Fig. 2. There are two things to note in this figure. First, some of the estimated parameters are quite different across regimes. Second, in some regimes, parameters are not identified, like the *Politician* variable in regimes 1 and 2. Here, our posterior inferences are being driven solely by our priors.

What do we make of these findings? It seems clear that a single identifiable jurisprudential regime likely does not exist in this domain, at least for these cases and with this set of covariates. The most

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Table 2 Estimated posterior probabilities of regime transitions for the freedom-of-expression model M_4

Regime	*CP*	*Case name*	*Date*	*USCite*	*Transition prob.*
I to II	103	*Peterson v. Greenville*	05/20/63	377 U.S. 244	.014
	114	*NLRB v. FVPW*	04/20/64	378 U.S. 58	.045
	115	*NAACP v. Alabama*	06/01/64	377 U.S. 288	.513
	116	*Baggett v. Bullitt*	06/01/64	377 U.S. 360	.364
	121	*Books v. Kansas*	06/22/64	378 U.S. 205	.012
	124	*Aptheker v. Secretary of State*	06/22/64	378 U.S. 500	.013
II to III	198	*Bryson v. US*	12/08/69	396 U.S. 64	.018
	199	*Jones v. TN Board of Education*	02/24/70	397 U.S. 31	.958
	219	*Connell v. Higginbotham*	06/07/71	403 U.S. 207	.017
III to IV	340	*Post v. NCCFB*	06/12/78	416 U.S. 775	.280
	341	*Houchins v. KQED*	06/26/78	436 U.S. 1	.129
	342	*FCC v. Pacifica Foundation*	07/03/78	438 U.S. 726	.174
	343	*Givhan v. Western Line*	01/04/79	438 U.S. 410	.032
	344	*Friedman v. Rogers*	02/21/79	440 U.S. 1	.051
	345	*TOA v. Rogers*	02/21/79	440 U.S. 1	.149
	346	*FCC v. Midwest Video*	04/02/79	440 U.S. 689	.073
	347	*ACLU v. FCC*	04/02/79	440 U.S. 689	.050
	348	*NBMC v. MVC*	04/02/79	440 U.S. 689	.058
IV to V	463	*Rotary Internation v. Rotary Club*	05/04/87	481 U.S. 537	.386
	464	*Turner v. Safley*	06/01/87	482 U.S. 78	.584
	465	*Houston v. Hill*	06/15/87	482 U.S. 451	.030

likely reason why the model is having difficulty finding a coherent change-point or set of change-points is that the cases Richards and Kritzer included in their study are too wide-ranging and disparate. Although all of them fall under the heading of the First Amendment, that heading is wide indeed and includes numerous different subheadings: subversive advocacy, obscenity, libel, and rights of association, to name just a few. It would be quite remarkable to learn that the law in all these areas developed in lockstep so that regime changes occurred simultaneously in all. We might find evidence to support the Richards-Kritzer conclusion in a more narrowly tailored set of cases. Once we endogenize the change-points, there is little evidence of a jurisprudential regime in freedom-of-expression cases. If we were to stop with just the free-speech cases, we would be very pessimistic about the empirical support for jurisprudential regimes. We see a very different story in the other three areas of law.

4.2 *Establishment Clause*

In another study, Kritzer and Richards (2003) examine cases surrounding the Establishment Clause of the First Amendment. They look at all cases decided from 1947 to 1999. In total, the Justices cast $N = 760$ votes during this time period. The key precedent in this area is *Lemon v. Kurtzman*, 403 U.S. 602 (1971). In *Lemon*, the Court provided a three-pronged test to determine whether or not a regulation violates the Establishment Clause: whether it has a secular purpose, whether its effect "neither advances or inhibits" religion, and whether the regulation does not foster "excessive government entanglement" with religion.

In Table 3, we report the results from our Bayesian model comparison. There is strong support that a model with a single change-point is the best model. Again, when just comparing the pooled probit model with the deterministic change-point, the parsimonious pooled model is selected. Where is the change-point located? Figure 3 shows the time-series plots of the regime shift. The single regime transition starts at decision time 19 (the 19th case), and the transition is complete at time 22. All cases before time 19 are certainly in regime 1, and those after time 22 are in regime 2 with probability one. The cases in between are transition cases, with the most likely change-point

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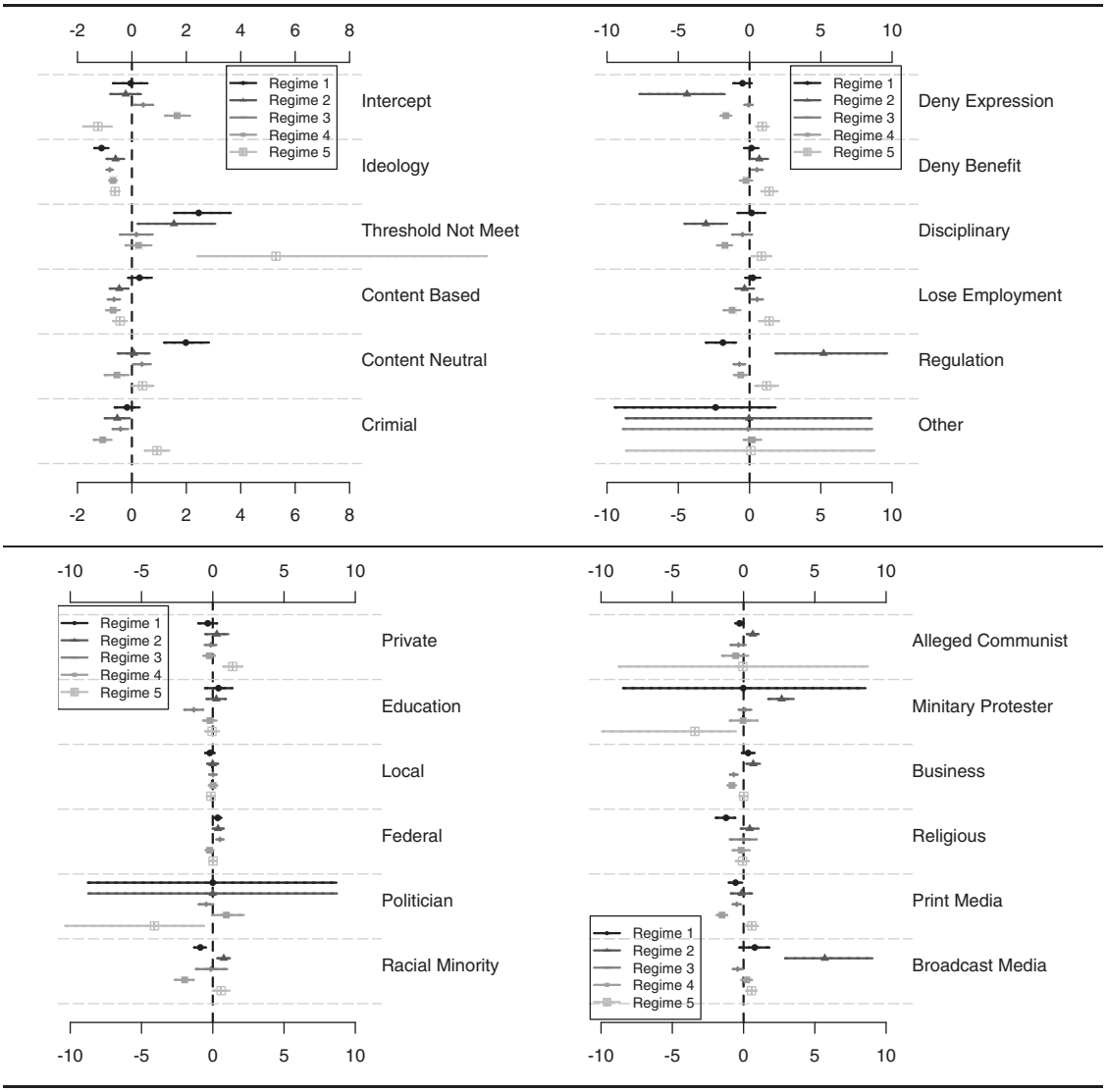


Fig. 2 Posterior density summaries of probit coefficients from a multivariate multiple change-point probit model M_4. Horizontal bars represent 95% credible intervals. The points indicate posterior mean. Dependent variable is coded 1 if the Justice votes to uphold the regulation and 0 otherwise. $N = 4986$.

case at time 20 (the 20th case with transition probability .8), indicated by the spike in the lower panel. Table 4 shows that the 20th case is *Norwood*, which is a very sharp change-point that occurs right after the 19th case, *Lemon*; that is, the case that first applied the *Lemon* test. These results are very strong evidence of a marked shift that happened right after the *Lemon* decision.

What about the structural parameters? In Fig. 4, we report the probit parameters for the two regimes. Our substantive estimates essentially mirror those found by Kritzer and Richards (2003). There are significant differences in some key covariates. The no-secular-purpose test was positive in regime 1 and negative in regime 2 once the *Lemon* test was in place. In regime 1, historical practices were significantly more likely to be allowed; in regime 2, the marginal effect is not distinguishable from zero. These substantively meaningful changes, along with the strong evidence for the location of the break, suggest that in this application, the *Lemon* case established a jurisprudential regime. This finding is consistent with Scott (2006), who provides more nuanced test of the *Lemon* regime, finding that even those Justices who did not support the *Lemon* rule initially exhibited patterns of behavior consistent with the jurisprudential regime thesis.

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Table 3 Log-marginal likelihoods and Bayes's factors for the Establishment Clause results

Model	*Number of changing points*	*Marginal likelihood* (log_e)	*Bayes's factor* ($log_{10}B_{M,\ M_1}$)
M_0	0 (Pooled Probit)	−464.015	−1.722
$M_{1'}$	1 (Deterministic)	−470.565	−4.566
M_1	1 (Probabilistic)	−460.051	−.−
M_2	2 (Probabilistic)	−465.076	−2.182

Note. In the log Bayes's factor, the marginal likelihood of M_1 is in the denominator, and a negative log-BF means that M_1 is favored by the data. The results are from a multivariate multiple change-point probit model. $N = 760$

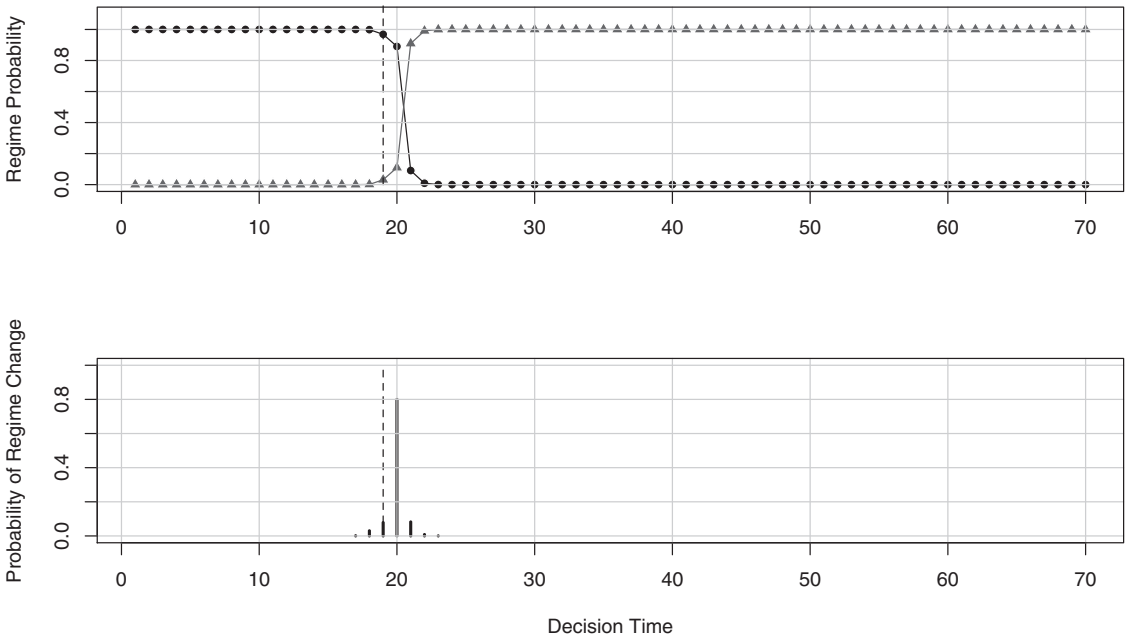


Fig. 3 Regime change and probabilities of regime-change time-series plots for Establishment Clause model M_1. The vertical dashed line denotes *Lemon*.

4.3 *Search-and-Seizure*

Kritzer and Richards (2005) return to the search-and-seizure data collected by Segal (1986). They use data from 228 cases from 1962 through 2001, a total of $N = 1969$ votes. Segal provides a parsimonious set of covariates that have been shown to explain a great deal of variance in voting in the search-and-seizure domain. Kritzer and Richards (2005) posit that the key shift in search-and-seizure jurisprudence took place in a set of cases in 1984 when the good-faith exception to the exclusionary rule was introduced. The change is not sharply demarcated by a single case. Rather, they identify a series of cases beginning with *Illinois v. Gates*, 462 U.S. 213 (1983). This would suggest that the model might show some uncertainty about the location of the break.

In Table 5, we report the model comparison results. Just as with the Establishment Clause models, the data best support a single, probabilistic change-point. When does the break take place? We can first look at Fig. 5. The figure shows that there are two most likely transition cases (the 49th and the 50th cases), and all other cases are stable in either regime 1 or regime 2. Then, when did the transition occur? Table 6 shows that the break does not occur in 1984, as Kritzer and Richards (2005) argue. To the contrary, the break takes place after a pair of cases decided at the end of the 1971 term.

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Table 4 Estimated posterior probabilities of regime transitions for the Establishment Clause model M_1

Regime	*CP*	*Case name*	*Date*	*USCite*	*Transition prob.*
I to II	19	*Lemon et al. v. Kurtzman*	04/02/73	411 U.S. 192	.078
	20	*Norwood et al. v. Harrison et al.*	06/25/73	413 U.S. 455	.800
	21	*Levitt, et al. v. Education et al.*	06/25/73	413 U.S. 472	.082

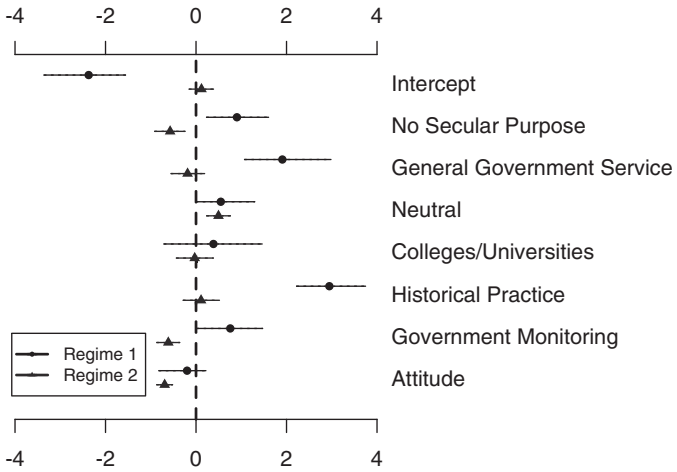


Fig. 4 Posterior density summaries of probit coefficients from a multivariate multiple change-point probit model M_1. Horizontal bars represent 95% credible intervals. Dependent variable is coded 1 if the Justice votes to accommodate the religious group and 0 otherwise. $N = 760$.

Table 5 Log-marginal likelihoods and Bayes's factors for the search-and-seizure results

Model	*Number of changing points*	*Marginal likelihood* (log_e)	*Bayes's factor* (log_{10}) (log_{10} $B_{M,\ M_1}$)
M_0	0 (Pooled Probit)	−1175.178	−9.195
M_1	1 (Probabilistic)	−1154.005	−.−
M_2	2 (Probabilistic)	−1166.419	−5.391
M_3	3 (Probabilistic)	−1166.673	−5.502
M_4	4 (Probabilistic)	−1170.952	−7.360

Note. In the log Bayes's factor, the marginal likelihood of M_1 is in the denominator, and a negative log-BF means that M_1 is favored by the data. The results are from a multivariate multiple change-point probit model. $N = 1969$

Figure 6 shows the estimates of the probit coefficients in each regime. There are some differences across regimes. There is a starkly different baseline rate of the search being upheld (captured by the intercept) between regimes, and in regime 2 the magnitude of effect of nearly every covariate is muted, except for the attitudes of the Justices.

The most likely explanation for the sharp regime change in 1972 involves political factors more than jurisprudential ones. In 1968, Richard Nixon ran for President on a "law and order" platform that included attacks on the Supreme Court's criminal procedure decisions. Immediately after he took office in 1969, he appointed the conservative Warren Burger to replace Earl Warren as Chief Justice, and Harry Blackmun to replace Abe Fortas. Then, two additional Nixon Justices took their seats in early January 1972, just before the regime change identified in the model. These Justices were William Rehnquist and Lewis Powell. Given popular support for Nixon's law-and-order

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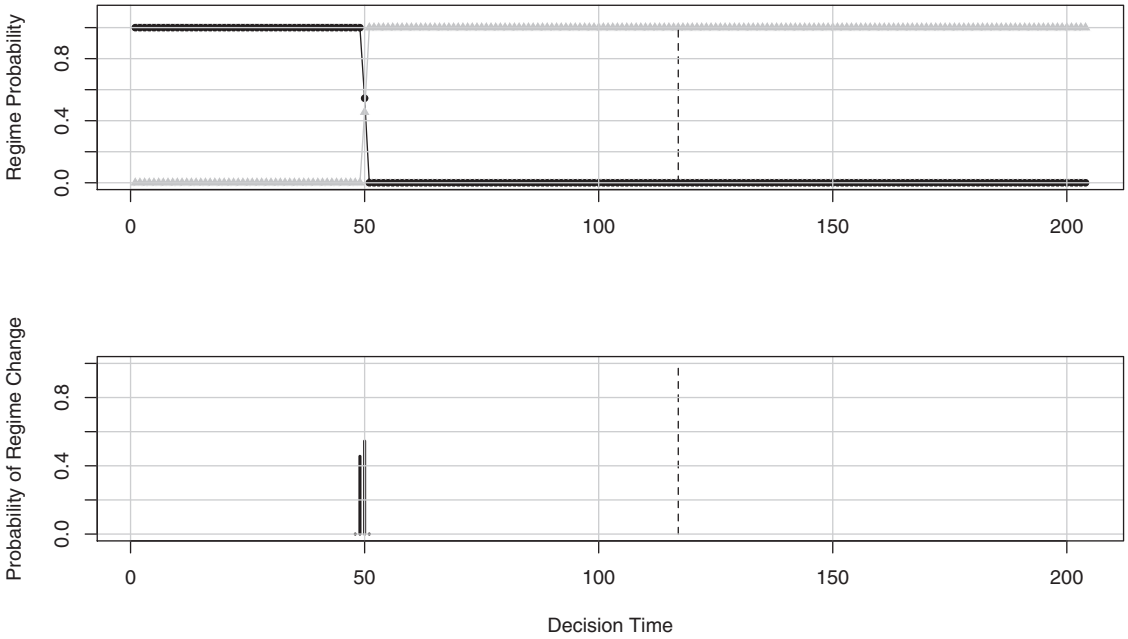


Fig. 5 Regime change and probabilities of regime-change time-series plots for the search-and-seizure model M_1. The vertical dashed line denotes *Gates*.

Table 6 Estimated posterior probabilities of regime transitions for the search-and-seizure model M_1

Regime	*CP*	*Case name*	*Date*	*USCite*	*Transition prob.*
I to II	49	*Adams v. Willams*	06/19/72	407 US 297	.455
	50	*Shadwick v. Tampa*	06/19/72	407 US 345	.545

views, and his ability to appoint so many Justices, it is perhaps of little surprise that search-and-seizure took the turn it did.

4.4 *Administrative Law*

In the area of administrative law, the *Chevron U.S.A. Inc. v. Natural Resources Defense Council, Inc.*, 467 U.S. 837 (1984), decision plays a crucial role. As Richards, Smith, and Kritzer (2006) write:

> In *Chevron*, the Court tackled the question of the appropriate level of deference that courts should give to statutory interpretations made by administrative and regulatory agencies. Prior to this decision, the Court had not given definitive direction to lower courts charged with determining whether agency interpretations were valid ... The Court attempted to clarify these conflicting lines of cases by ruling in *Chevron* ... that unless Congress has spoken to the precise question at issue, any reasonable interpretation by the agency must be upheld. (pp. 445–46)

The test is two-pronged. Judges first must look to Congress and see whether it has spoken unambigiously. If it has, the the court must ensure the agency is doing what Congress asked. Otherwise, the court must defer to the agency, unless the agency's interpretation of the statute is unreasonable. While there is some debate about whether *Chevron* actually eliminates political bias from judging regarding administrative agencies (Miles and Sunstein 2006), it is certainly the case that today the *Chevron* case is one of the most cited case in administrative law. Richards, Smith, and Kritzer (2006) study all cases from 1969 to 2000 in the area of administrative law. They included a total of $N = 1129$ votes in their analysis.

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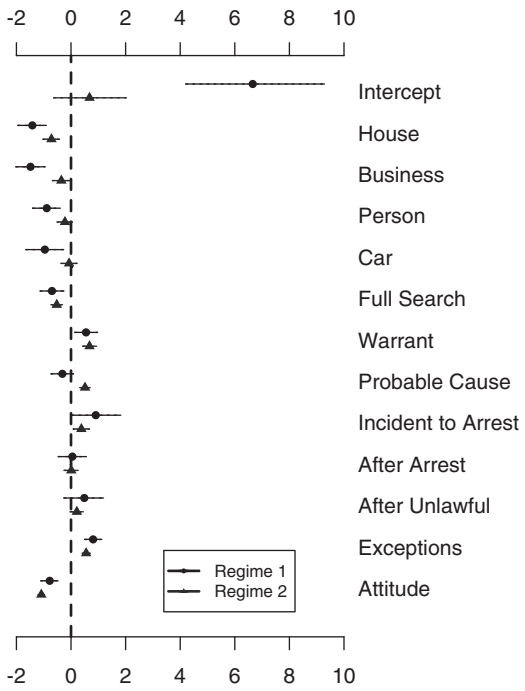


Fig. 6 Posterior density summaries of probit coefficients from a multivariate multiple change-point probit model M_1. Horizontal bars represent 95% credible intervals. Dependent variable is coded 1 if the Justice votes to uphold the search and 0 otherwise. $N = 1969$.

Table 7 contains the model comparison results. Again, a single change-point model is best supported by the data. However, Fig. 7 shows that the regime transition is slow, spanning 16 decision times from the 33rd case to the 55th case. The lower panel shows that the transition probability spikes at the 34th and 55th cases, about six years away from each other. Table 8 reports the names and dates of the cases with transition probability no less than .001. Two things are clear. First, the model is very uncertain about where the break takes place. The break does not reside in a single case, or even in a single time period. The model suggests the break took place sometime between 1978 and 1984. *Chevron* was decided on June 25, 1984. Second, there are some discontinuities in the cases with positive probabilities of being the change-point; for example, cases 35–38 received no positive probability, and neither does case 50. While the model does not select *Chevron*, it is close.

We report the structural parameters in Fig. 8. Just as with the original Richards, Smith, and Kritzer (2006) study, there are some differences before and after the regime change. The baseline rate of upholding agency decisions increased significantly after *Chevron*. Before *Chevron*, a corporation opposing deference increases the likelihood of deference in regime 1; the effect is far smaller in regime 2. While the location of the change-point slightly predates *Chevron*, the estimated structural parameters are quite similar.

These results may lend some support to the idea that *Chevron* created a jurisprudential regime, but we are a bit skeptical that the results support Kritzer and Richard's conclusion. There is an ongoing debate in administrative law about whether Chevron was intended to signal a regime change or was decided on the basis of principles immanent in administrative law for some time. But no literature with which we are familiar suggests that Chevron was simply the culmination of decisions that preceded it with some immediacy. Similarly, although Chevron undoubtedly had an effect in the lower courts, studies have not been so certain on the Supreme Court, and the Chevron jurisprudence continues to evolve. If the model had picked a change-point at Chevron, as was the case with the *Lemon* test in the Establishment Clause jurisprudence, we would be more confident that Chevron signaled a regime case. Given the results we find, one is less confident.

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Table 7 Log-marginal likelihoods and Bayes's factors for the administrative law results

Model	*Number of changing points*	*Marginal likelihood* (log_e)	*Bayes's factor* (log_{10} $B_{M,\ M_1}$)
M_0	0 (Pooled Probit)	−778.566	−15.660
$M_{1'}$	1 (Deterministic)	−771.478	−12.582
M_1	1 (Probabilistic)	−742.507	−.−-
M_2	2 (Probabilistic)	−759.396	−7.335
M_3	3 (Probabilistic)	−797.080	−23.701

Note. In the log Bayes's factor, the marginal likelihood of M_1 is in the denominator, and a negative log-BF means that M_1 is favored by the data. The results are from a multivariate multiple change-point probit model. $N = 1129$.

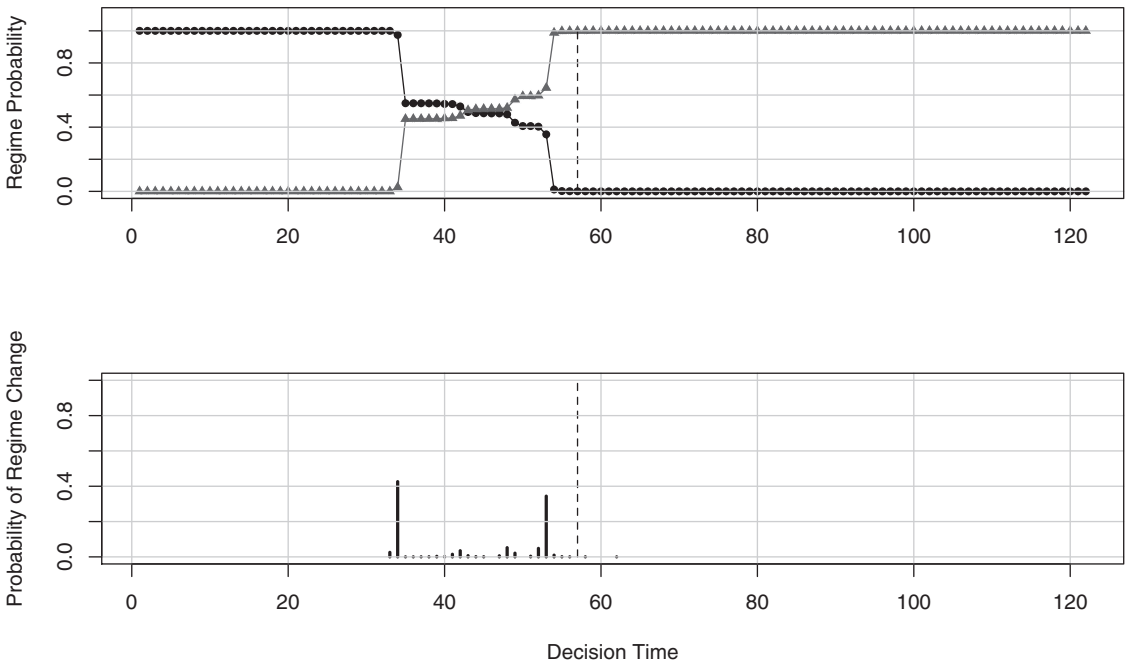


Fig. 7 Regime change and probabilities of regime-change time-series plots for administrative law model M_1. The vertical dashed line denotes *Chevron*.

5 Conclusion

The modeling strategy proposed in this article allows us to endogenously determine whether or not there are structural breaks in probit regression models for multivariate data when decisions are made in order, as they are on the Supreme Court. This modeling strategy allows us to endogenously estimate the locations and number of change-points in these data. This provides the strongest test to date of the jurisprudential regime hypotheses.

Taken as a whole, what have we learned about jurisprudential regimes from this approach? In the Establishment Clause context, our results support the conclusions of Kritzer and Richards (2003) that *Lemon* established a regime in the Establishment Clause context, and suggest with Richards, Smith, and Kritzer (2006) that *Chevron* might have done the same in administrative law. In two other areas, however, the model shows that previous results were mere artifacts. In the free-speech context, the model finds five regimes over the fifty-year study. In search-and-seizure, the model locates the change-point far earlier than hypothesized. One might ask why this is the case.

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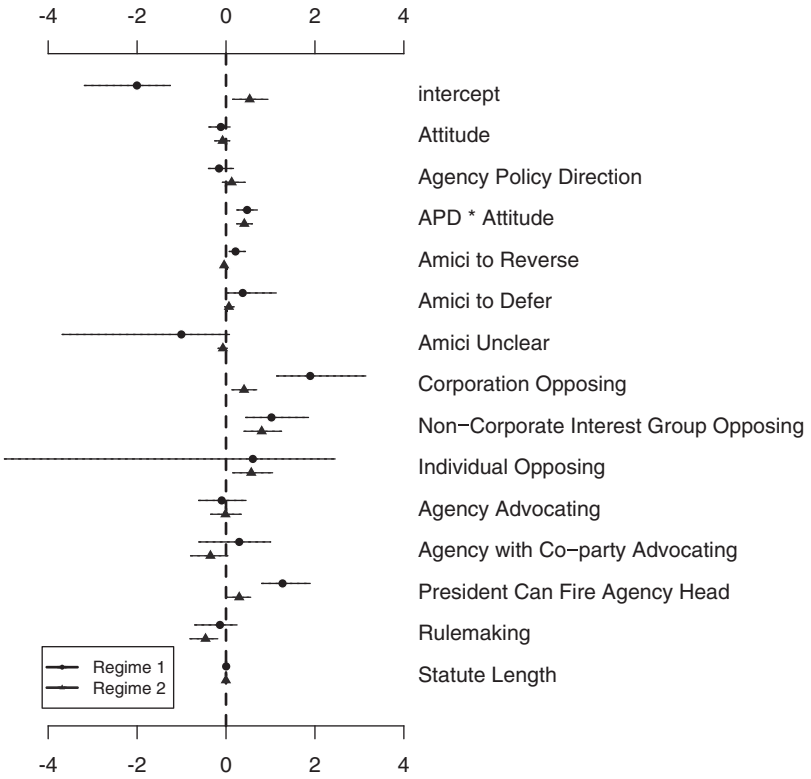


Fig. 8 Posterior density summaries of probit coefficients from a multivariate multiple change-point probit model M_1. Horizontal bars represent 95% credible intervals. Dependent variable is coded 1 if the Justice votes to defer to the agency and 0 otherwise. $N = 1129$.

Table 8 Estimated posterior probabilities of regime transitions for the administrative law model M_1

Regime	*CP*	*Case name*	*Date*	*USCite*	*Transition prob.*
I to II	33	*Securitues v. SLOAN*	05/15/78	436 U.S. 103	.025
	34	*ANDRUS v. Charlestone*	05/31/78	436 U.S. 604	.426
	39	*Watt, et al. v. Energy et al.*	12/01/81	454 U.S. 151	.003
	40	*North Haven et al. v. Bell, et al.*	05/17/82	456 U.S. 512	.001
	41	*State et al. v. Washington Post*	05/17/82	456 U.S. 595	.015
	42	*Federal Bureau et al. v. Abramson*	05/24/82	456 U.S. 615	.035
	43	*Education, et al. v. Rowley*	06/28/82	458 U.S. 176	.007
	44	*Community Tel v. Gotifried et al.*	02/22/83	459 U.S. 498	.001
	47	*Trade Commision et al. v. Grolier*	06/06/83	462 U.S. 19	.006
	48	*Bank America. et al. v. U.S.*	06/08/83	462 U.S. 122	.052
	49	*Chappell. v. Wallace et al.*	06/13/83	462 U.S. 296	.021
	51	*A.T.F v. Labor Relations et al.*	11/29/83	464 U.S. 89	.004
	52	*U.S. v. Weber Aircraft. et al.*	03/20/84	465 U.S. 792	.048
	53	*Equal Employment v. Shell*	04/02/84	466 U.S. 54	.344
	54	*Trans World v. Franklin Mint et al.*	04/17/84	466 U.S. 243	.010
	55	*Communications et al. v. ITT, et al.*	04/30/84	466 U.S. 463	.001

Does this mean we should give up on the idea of jurisprudential regimes? Absolutely not. This theory is the most plausible empirical legal model of decision-making to date. It enjoys some support in some areas of law, just as the fact-pattern models of an earlier generation. Just because the theory does not work in some contexts does not mean we should give up on it. It is implausible that legal considerations do not affect decision-making with regard to judgments on the

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Supreme Court. And even if they did, studying the craft of decision-making with regard to writing opinions and creating legal rules remains central to the positive study of the Supreme Court.

Looking at subsequent behavior on the Supreme Court most likely is not the best place to look to measure the effects of a jurisprudential regime. Studying the lower courts, on the other hand, would likely be very promising. Of course, finding these effects there would confirm the existence of vertical *stare decisis*, about which there is little debate. Nonetheless, a study of the effects of a key Supreme Court precedent would tell us something important about vertical *stare decisis* and how well it operates, including whether certain types of rules—such as bright-line rules—engender greater compliance.

The methodological approach described here has applications far beyond the judicial politics context. The multiple change-point model for multivariate time-series data can be used when a committee of any size votes on items in some sequence. Rather than having to specify in advance how the effects of the covariates might change over time, the model finds the interactions that are best supported by the data. This, coupled with the Bayesian tools for nonnested model testing, provides the most flexible way to understand these dynamics. Our model is a type of mixture model that allows for differential effects across groups or across time, which can be applied even if the group identifiers or the change-points are unknown (Hill and Kriesi 2001). In addition, because the model we propose in the article handles irregular and multivariate time series, it has broad potential applications to studying other institutions or processes that happen irregularly through time.

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