Endogenous Jurisprudential Regimes*

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Abstract

Jurisprudential regime theory (Richards and Kritzer, 2002) 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 paper we offer a multivariate multiple change-point probit model that can be used to endogenously test for the existence of jurisprudential regimes. It does so by estimating the location of possibly many change-points along with structural parameters. We estimate the model using Markov chain Monte Carlo methods, and use Bayes factors for formal model comparison. 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.

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1 Modeling Decisionmaking on the U.S. Supreme Court

Supreme Court decisions do two things: they award a judgment, and they provide a rational 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.

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 doesn’t 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 which is used by others.

In order to adequately model decisionmaking on the Supreme Court, it’s 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’s 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 opinion. There is some related empirical literature about modeling various legal choices, such as issues of standing (Pierce, 1998-1999; 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 paper 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 paper 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 become difficult to know whether the decisions are grounded in “law” or something else—be it judicial preferences, concerns about external pressures, or the like. While
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,b). In its simplest form, this model formalizes the relationship among rules, the facts of the case, and the disposition that provide guidance when it comes to trying to control for law as in independent explanation of outcomes. 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. (2007) provide an alternative formal model of decisionmaking that incorporates trade-offs 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 merits 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 of 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 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 this may be descriptively the case, we are left wondering what mechanism is in place. When casting votes on the merits, how do justices weigh the legal factors; i.e., 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 “...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...” (Richards and Kritzer, 2002, p. 306). In other words, it is not the factual circumstances of a prior precedent that matters so much as the doctrinal test set up 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, p. 308). The basic idea is that after a key precedent, we would expect to see the patterns of decisionmaking 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 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”; e.g., Berkemer v. McCarty, 468 U.S. 420 (1984) that 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 regimes 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 merits 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. Another covariate is the ideology of each justice; Richards and Kritzer use the scores developed by Segal and Cover (1989).
The empirical strategy is straightforward. In essence, Kritzer and Richards ask: does ideology 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. The Chow (1960) 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, 2005), and administrative law (Richards, Smith and Kritzer, 2006). We’ll 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 are used 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. Finally, the Chow (1960) test that is used is falsely discriminatory (Lax and Rader, 2010), and doesn’t entertain the possibility of multiple breaks or breaks located elsewhere. In their re-analysis 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 votes in subsequent cases” (p. 282). 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.

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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 decisionmaking 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 changepoint is incorrect.
3 Endogenous Jurisprudential Regimes with a Probit Multiple Change-Point Model

Our purpose in this paper 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 require specifying \textit{ex ante} the location of the change-point. Second, it would not assume that a single change-point exists; it would allow the possibility of multiple change-points. These two features would allow the data to speak about the existence, or not, of the 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 are 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 regime”, we use the same datasets in 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. 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 paper 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 4,986 votes within 570 cases over 38 years. How can we be so sure that \textit{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 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 pre-determined—Grayned v. Rockford, 408 U.S. 104 (1972) (in freedom of speech), Lemon v. Kurtzman, 403 U.S. 602 (1971) (in religious establishment), a number of cases including Segura v. U.S., 468 U.S. 796 (1983) (in search-and-seizure), 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 neighborhood cases as alternative change-points. But most of the cases are still out of consideration. Furthermore, as Lax and Rader (2010) pointed out, this kind of robustness check is not convincing since the neighborhood observations are expected to produce similar testing results.

Third, how confident are we about the estimated number and locations 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 can 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 to one another; these models will not be nested. We adopt a fully Bayesian modeling strategy, and use Bayes 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 (for example, Carlin, Gelfand and Smith, 1992; Barry and Hartigan, 1993; Chib, 1996, 1998; Hawkins, 2001; Minin et al., 2005). In political science, single (Spirling, 2007) and multiple (Brandt and Sandler, 2010; Park, 2010) change-point models have been increasingly applied to detect structural breaks and improve model-fitting. In the literature, there are various ways to parametrize a multiple change-point model. Here, we apply the one introduced by 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 change to 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. This is a restrictive assumption. Nonetheless, the question under investigation is whether precedents change the Supreme Court decisionmaking 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 re-
cover three regimes, with structural parameters the same, up to sampling error, in the first and last regimes.

We model the process of regime evolution using a discrete multivariate random variable $S = \{s_1, ..., s_t, ..., s_T\}$. This variable indicates in what regime an observation is. Its probability function can be built up from the conditional probabilities $\Pr(s_t = k | s_{t-1} = k) = p_{k,k}$ and $\Pr(s_t = k + 1 | s_{t-1} = k) = p_{k,k+1} = 1 - p_{k,k}$. In this setup, the change-points are easy to locate once we know $S$. By definition, a change-point from regime $k$ to regime $k + 1$, $\tau_k$, 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 $i, j = 1, ..., T$. This model we propose directly estimates the latent discrete regime states $S$ and locates all the change-points.

This multiple change-point model can also address the important question of what determining $K$—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 $\Pr(\mathcal{M} | K, Y)$ with $=K\{0,1,...,J\}$. The posterior of $K$ is $\Pr(K | M, Y) \propto \Pr(\mathcal{M} | K, Y)\Pr(K)$, with a discrete uniform prior of $K$, then $\Pr(K = j | \mathcal{M}, Y) = \Pr(\mathcal{M} | K = j, Y) / \sum_{k=0}^{J} \Pr(\mathcal{M} | K = k, Y)$. That is, we can use model comparison with 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 ($S$) is generated; given $S$, the regime-specific 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 $\Upsilon_K = \{\tau_1, ..., \tau_K\}$. 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 $Y_T = \{y_1, y_2, ..., y_T\}$ is a multivariate time-series, and $y_t$ is a $n_t$-dimensional vector. In the present paper, $t$ indicates the date of the decision, $y_t$ are the votes on the judgment, and $n_t$ is the number of justices at decision time $t$. $n_t$ 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.

The joint distribution of \( y_t \) given \( Y_{t-1} = \{y_1, y_2, \ldots, y_{t-1}\} \) depends on a parameter vector \( \Theta \) that changes at unknown time periods \( \Upsilon_K = \{\tau_1, \ldots, \tau_K\} \), where \( \tau_1 > 1 \) and \( \tau_K < T \):

\[
\Theta = \begin{cases} 
\Theta_1 & \text{if } t \leq \tau_1 \\
\Theta_2 & \text{if } \tau_1 < t \leq \tau_2 \\
\vdots & \vdots \\
\Theta_K & \text{if } \tau_{K-1} < t \leq \tau_K \\
\Theta_{K+1} & \text{if } \tau_K < t \leq T 
\end{cases}
\]

With the state variable \( S_t \), the probit multiple changing-point model can be specified as follows:

\[
y_{i,t} = \mathbb{I}(z_{i,t} > 0), \quad i = 1, \ldots, n_t, \ t = 1, \ldots, T \tag{1}
\]

\[
z_{i,t} = x_{i,t}' \beta_{s_t} + \xi_{i,t}, \tag{2}
\]

\[
\xi_{i,t} \sim N_{n_t}(0, I). \tag{3}
\]

This looks exactly like a regular probit model except that the coefficients \( \beta \) has a subscript \( s_t \) so that in equation (2) \( \beta_{s_t} \) is a regime-specific coefficient vector. If \( y_{i,t} \) belongs to regime \( s_t \), it is generated by the coefficients \( \beta_{s_t} \). 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 dimension of the parameter space in different regimes. This is one advantage of using a Bayesian inferential approach.

The variable \( s_t \) follows a Markov process with transition matrix:

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

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

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 \textit{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 \( z_{i,t} = x_{i,t}' \beta_{s_t} + b_t + b_p + \xi_{i,t} \), where \( b_t \) is the decision-time-specific effect
and $b_p$ 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 9 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:

$$f(\beta, S, P | Y) \propto \left( \prod_{s,t} f(y_{s,t} | \beta_{s,t}) \pi(\beta_{s,t}) \right) p(S | P) \pi(P)$$

We use $p_{ii} \sim \text{Beta}(1, 1)$ priors that are 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 informative priors. In general, our preference is to use informative priors when we have them. For the coefficients $\beta_{s,t}$, we use the same prior distribution for all regimes, $N(\bar{\beta}_0, B_0)$ where $\bar{\beta}_0 = 0$ and $B_0 = 100 \times I$. To estimate the model, we apply and modify the algorithm developed in Chib (1998) to deal with our grouped time series. We present the detailed Markov chain Monte Carlo algorithm for estimating a general clustered multiple change-point model in Appendix A. The posterior draws give us all the necessary information about the probability of regime change at each time period ($S$), and how different the regimes are is reflected by the regime-specific structural parameters.

### 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). The approach we used 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 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 caused a decrease in model quality. For each model we compute the log-marginal likelihood, and ultimately choose the model with the highest posterior probability.$^3$

$^3$Suppose that the true data-generating process has $K = 6$. This approach would never find that 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
To compare the models with different numbers of change-points we use the Bayes factor. Suppose that the observed data $Y$ 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 theorem, we have:

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

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

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

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-side hand, which is called the Bayes factor:

$$
B_{12} = \frac{p(Y|\mathcal{M}_1)}{p(Y|\mathcal{M}_2)}
$$

We require the marginal likelihood of competing models to compute the Bayes factors. The marginal likelihood is defined as:

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

To handle this high-dimensional integration problem, we use the marginal likelihood approach proposed by Chib (1995) to approximate the marginal likelihood. We posit the detailed MCMC scheme for estimating the marginal likelihood in Appendix B.

### 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 then a series of models where the change-points are probabilistically estimated starting at $K = 1$ and increasing the value of $K$ and re-estimating the $i$ 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.
model until the performance degrades. For each we compute and show the log-marginal likelihoods. Since all of the models are of the same data \( Y \), all can be compared using Bayes factors.\(^4\)

For the best performing model, we graphically report the location(s) of the change-point, and the structural parameters within each regime.\(^5\)

### 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 in 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 \textit{Chicago Police Department v. Mosley}, 408 U.S. 92 (1972) and \textit{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 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 Chow 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; i.e., five regimes where there are substantial differences in structural parameters.

In Table 2 we report the locations of the regime transitions in these data. Do these make substantive sense? Not really. The model misses the \textit{Grayned} transition in 1972. The transition from Regime I to Regime II is close to the \textit{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

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\(^4\)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 of different data.

\(^5\)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.
<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Changing Points</th>
<th>Marginal Likelihood (ln)</th>
<th>Bayes Factor (log$_{10}$) $M_4$ as Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_0$</td>
<td>0 (Pooled Probit)</td>
<td>$-3069.149$</td>
<td>$-25.306$</td>
</tr>
<tr>
<td>$M_1'$</td>
<td>1 (Deterministic)</td>
<td>$-3281.109$</td>
<td>$-117.360$</td>
</tr>
<tr>
<td>$M_1$</td>
<td>1 (Probabilistic)</td>
<td>$-3069.627$</td>
<td>$-25.513$</td>
</tr>
<tr>
<td>$M_2$</td>
<td>2 (Probabilistic)</td>
<td>$-3072.921$</td>
<td>$-26.944$</td>
</tr>
<tr>
<td>$M_3$</td>
<td>3 (Probabilistic)</td>
<td>$-3048.649$</td>
<td>$-16.399$</td>
</tr>
<tr>
<td>$M_4$</td>
<td>4 (Probabilistic)</td>
<td>$-3010.880$</td>
<td>$-.$</td>
</tr>
<tr>
<td>$M_5$</td>
<td>5 (Probabilistic)</td>
<td>$-3028.911$</td>
<td>$-7.831$</td>
</tr>
<tr>
<td>$M_6$</td>
<td>6 (Probabilistic)</td>
<td>$-3031.344$</td>
<td>$-8.887$</td>
</tr>
</tbody>
</table>

Table 1. Log-marginal likelihoods and Bayes factors for the freedom of expression results. The results are from a multivariate multiple change-point probit model. $N = 4986$.

*Brandenburg v. Ohio*, 395 U.S. 444 (1969) case where the Court held that the government cannot regulate speech unless it is likely to provide “imminent lawless action” and the *Schacht v. United States*, 398 U.S. 58 (1970) decision which held 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 anti-war 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. Figure 1 contains the time series plots of the locations of the regimes.
<table>
<thead>
<tr>
<th>Regime</th>
<th>CP</th>
<th>CaseName</th>
<th>Date</th>
<th>USCite</th>
<th>Transition Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>I to II</td>
<td>103</td>
<td>Peterson v. Greenville</td>
<td>05/20/63</td>
<td>377 U.S. 244</td>
<td>0.014</td>
</tr>
<tr>
<td></td>
<td>114</td>
<td>NLRB v. FVPW</td>
<td>04/20/64</td>
<td>378 U.S. 58</td>
<td>0.045</td>
</tr>
<tr>
<td></td>
<td>115</td>
<td>NAACP v. Alabama</td>
<td>06/01/64</td>
<td>377 U.S. 288</td>
<td>0.513</td>
</tr>
<tr>
<td></td>
<td>116</td>
<td>Baggett v. Bullitt</td>
<td>06/01/64</td>
<td>377 U.S. 360</td>
<td>0.364</td>
</tr>
<tr>
<td></td>
<td>121</td>
<td>Books v. Kansas</td>
<td>06/22/64</td>
<td>378 U.S. 205</td>
<td>0.012</td>
</tr>
<tr>
<td></td>
<td>124</td>
<td>Aptheker v. Secretary of State</td>
<td>06/22/64</td>
<td>378 U.S. 500</td>
<td>0.013</td>
</tr>
<tr>
<td>II to III</td>
<td>198</td>
<td>Bryson v. US</td>
<td>12/08/69</td>
<td>396 U.S. 64</td>
<td>0.018</td>
</tr>
<tr>
<td></td>
<td>199</td>
<td>Jones v. TN Board of Education</td>
<td>02/24/70</td>
<td>397 U.S. 31</td>
<td>0.958</td>
</tr>
<tr>
<td></td>
<td>219</td>
<td>Connell v. Higginbotham</td>
<td>06/07/71</td>
<td>403 U.S. 207</td>
<td>0.017</td>
</tr>
<tr>
<td>III to IV</td>
<td>340</td>
<td>Post v. NCCFB</td>
<td>06/12/78</td>
<td>416 U.S. 775</td>
<td>0.28</td>
</tr>
<tr>
<td></td>
<td>341</td>
<td>Houchins v. KQED</td>
<td>06/26/78</td>
<td>436 U.S. 1</td>
<td>0.129</td>
</tr>
<tr>
<td></td>
<td>342</td>
<td>FCC v. Pacifica Foundation</td>
<td>07/03/78</td>
<td>438 U.S. 726</td>
<td>0.174</td>
</tr>
<tr>
<td></td>
<td>343</td>
<td>Givhan v. Western Line</td>
<td>01/04/79</td>
<td>438 U.S. 410</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>344</td>
<td>Friedman v. Rogers</td>
<td>02/21/79</td>
<td>440 U.S. 1</td>
<td>0.051</td>
</tr>
<tr>
<td></td>
<td>345</td>
<td>TOA v. Rogers</td>
<td>02/21/79</td>
<td>440 U.S. 1</td>
<td>0.149</td>
</tr>
<tr>
<td></td>
<td>346</td>
<td>FCC v. Midwest Video</td>
<td>04/02/79</td>
<td>440 U.S. 689</td>
<td>0.073</td>
</tr>
<tr>
<td></td>
<td>347</td>
<td>ACLU v. FCC</td>
<td>04/02/79</td>
<td>440 U.S. 689</td>
<td>0.05</td>
</tr>
<tr>
<td></td>
<td>348</td>
<td>NBMC v. MVC</td>
<td>04/02/79</td>
<td>440 U.S. 689</td>
<td>0.058</td>
</tr>
<tr>
<td>IV to V</td>
<td>463</td>
<td>Rotary Internation v. Rotary Club</td>
<td>05/04/87</td>
<td>481 U.S. 537</td>
<td>0.386</td>
</tr>
<tr>
<td></td>
<td>464</td>
<td>Turner v. Safler</td>
<td>06/01/87</td>
<td>482 U.S. 78</td>
<td>0.584</td>
</tr>
<tr>
<td></td>
<td>465</td>
<td>Houston v. Hill</td>
<td>06/15/87</td>
<td>482 U.S. 451</td>
<td>0.03</td>
</tr>
</tbody>
</table>

**Table 2.** Estimated posterior probabilities of regime transitions for the freedom of expression model $M_4$.

**Figure 1.** Regime change and probabilities of regime change time series plots for freedom of expression model $M_4$. 
Figure 2. Posterior density summaries of probit coefficients from a multivariate multiple change-point probit model $M_4$. Horizontal bars represent 95% credible intervals. Dependent variable is coded 1 if the justice votes to uphold the regulation and 0 otherwise. $N = 4986.$
For the sake of completeness we report the structural parameters for the free speech data in Figure 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? Very little, besides the conclusion that a jurisprudential regime does not likely exist in this domain, at least for these cases and with this set of covariates. We might find evidence in a more narrowly tailored set of cases, or if we developed a more inclusive list of possible covariates. 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.

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Changing Points</th>
<th>Marginal Likelihood (( \log_{10} ))</th>
<th>Bayes Factor (( \log_{10} )) M₁ as Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M₀ )</td>
<td>0 (Pooled Probit)</td>
<td>-464.015</td>
<td>-1.722</td>
</tr>
<tr>
<td>( M₁' )</td>
<td>1 (Deterministic)</td>
<td>-470.565</td>
<td>-4.566</td>
</tr>
<tr>
<td>( M₁ )</td>
<td>1 (Probabilistic)</td>
<td>-460.051</td>
<td>-.</td>
</tr>
<tr>
<td>( M₂ )</td>
<td>2 (Probabilistic)</td>
<td>-465.076</td>
<td>-2.182</td>
</tr>
</tbody>
</table>

Table 3. Log-marginal likelihoods and Bayes factors for the Establishment Clause results. The results are from a multivariate multiple change-point probit model. \( N = 760 \).

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? Table 4 shows a very sharp change-point that occurs
### Table 4. Estimated posterior probabilities of regime transitions for the Establishment Clause model $M_1$.

<table>
<thead>
<tr>
<th>Regime Change</th>
<th>Case Name</th>
<th>Date</th>
<th>USCite</th>
<th>Transition Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>I to II</td>
<td>Lemon et al. v. Kurtzman</td>
<td>04/02/73</td>
<td>411 U.S. 192</td>
<td>0.078</td>
</tr>
<tr>
<td></td>
<td>Norwood et al. v. Harrison et al.</td>
<td>6/25/73</td>
<td>413 U.S. 455</td>
<td>0.8</td>
</tr>
<tr>
<td></td>
<td>Levitt, et al. v. Education et al.</td>
<td>6/25/73</td>
<td>413 U.S. 472</td>
<td>0.062</td>
</tr>
</tbody>
</table>

right after the case that followed *Lemon*; i.e., the case that first applied the *Lemon* test. Figure 3 shows the time series plots of the regime shift. These results are very strong evidence of a marked shift that happened right after the *Lemon* decision.

![Figure 3. Regime change and probabilities of regime change time series plots for Establishment Clause model $M_1$.](image)

What about the structural parameters? In Figure 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 is 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 justice who did not support the *Lemon* rule
initially exhibit patterns of behavior consistent with the jurisprudential regimes thesis.

\[ \begin{align*}
\text{Regime 1} & \quad \text{Regime 2} \\
\text{Intercept} & \quad \text{No Secular Purpose} \\
\text{General Government Service} & \quad \text{Neutral} \\
\text{Colleges/Universities} & \quad \text{Historical Practice} \\
\text{Government Monitoring} & \quad \text{Attitude} \\
\end{align*} \]

**Figure 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. \( N = 760 \).
4.3 Search and Seizure

Kritzer and Richards (2005) return to the search and seizure data collected by Segal (1986). They used 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 supports a single, probabilistic change-point. When does the break take place? Not in 1984, as Kritzer and Richards (2005) argue. To the contrary, as Table 6 shows, the break takes place after a pair of cases decided at the end of the 1971 term. Figure 5 shows how quickly this change takes place. What about the structural parameters? 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. These findings suggest that the jurisprudential factors seemed to matter less after 1972, and that political attitudes mattered more.

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Changing Points</th>
<th>Marginal Likelihood (( \log_e ))</th>
<th>Bayes Factor (( \log_{10} ))</th>
<th>( M_1 ) as Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>( M_0 )</td>
<td>0 (Pooled Probit)</td>
<td>-1175.178</td>
<td>-9.195</td>
<td></td>
</tr>
<tr>
<td>( M_1 )</td>
<td>1 (Probabilistic)</td>
<td>-1154.005</td>
<td>-5.391</td>
<td></td>
</tr>
<tr>
<td>( M_2 )</td>
<td>2 (Probabilistic)</td>
<td>-1166.419</td>
<td>-5.502</td>
<td></td>
</tr>
<tr>
<td>( M_3 )</td>
<td>3 (Probabilistic)</td>
<td>-1166.673</td>
<td>-5.502</td>
<td></td>
</tr>
<tr>
<td>( M_4 )</td>
<td>4 (Probabilistic)</td>
<td>-1170.952</td>
<td>-7.360</td>
<td></td>
</tr>
</tbody>
</table>

**Table 5.** Log-marginal likelihoods and Bayes factors for the search and seizure results. The results are from a multivariate multiple change-point probit model. \( N = 1969 \).
<table>
<thead>
<tr>
<th>Regime</th>
<th>CP</th>
<th>Case Name</th>
<th>Date</th>
<th>USCite</th>
<th>Transition Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>I to II</td>
<td>49</td>
<td>Adams v. Williams</td>
<td>06/19/72</td>
<td>407 US 297</td>
<td>0.455</td>
</tr>
<tr>
<td></td>
<td>50</td>
<td>Shadwick v. Tampa</td>
<td>06/19/72</td>
<td>407 US 345</td>
<td>0.545</td>
</tr>
</tbody>
</table>

**Table 6.** Estimated posterior probabilities of regime transitions for the search and seizure model $M_1$. 

**Figure 5.** Regime change and probabilities of regime change time series plots for the search and seizure model $M_1$. 
Figure 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. $N = 1969$. 

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4.4 Administrative Law


“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. 445-446)

The test is two-pronged. Judges first must look to Congress see whether it has spoken unambiguously. 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.

<table>
<thead>
<tr>
<th>Model</th>
<th>Number of Changing Points</th>
<th>Marginal Likelihood ($\log_{10}$)</th>
<th>Bayes Factor ($\log_{10}$) $M_1$ as Baseline</th>
</tr>
</thead>
<tbody>
<tr>
<td>$M_0$</td>
<td>0 (Pooled Probit)</td>
<td>$-778.566$</td>
<td>$-15.660$</td>
</tr>
<tr>
<td>$M_1'$</td>
<td>1 (Deterministic)</td>
<td>$-771.478$</td>
<td>$-12.582$</td>
</tr>
<tr>
<td>$M_1$</td>
<td>1 (Probabilistic)</td>
<td>$-742.507$</td>
<td>$-7.335$</td>
</tr>
<tr>
<td>$M_2$</td>
<td>2 (Probabilistic)</td>
<td>$-759.396$</td>
<td>$-7.335$</td>
</tr>
<tr>
<td>$M_3$</td>
<td>3 (Probabilistic)</td>
<td>$-797.0801$</td>
<td>$-23.701$</td>
</tr>
</tbody>
</table>

**Table 7.** Log-marginal likelihoods and Bayes factors for the administrative law results. The results are from a multivariate multiple change-point probit model. $N = 1129$.

Table 7 contains the model comparison results. Again, a single change-point model is best supported by the data. Table 8 shows the cases that with some positive probability of being the change-point. 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 the 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; e.g., cases 35-38 are receive no positive probability, and neither does case 50. The time series plot in Figure 7 shows the wide time interval where the change might be located. While the model does not select *Chevron*, it is close

<table>
<thead>
<tr>
<th>Regime</th>
<th>CP</th>
<th>CaseName</th>
<th>Date</th>
<th>USCite</th>
<th>Transition Probability</th>
</tr>
</thead>
<tbody>
<tr>
<td>I to II</td>
<td>33</td>
<td>Securitues v. SLOAN</td>
<td>05/15/78</td>
<td>436 U.S. 103</td>
<td>0.025</td>
</tr>
<tr>
<td></td>
<td>34</td>
<td>ANDRUS v. Charleston</td>
<td>05/31/78</td>
<td>436 U.S. 604</td>
<td>0.003</td>
</tr>
<tr>
<td></td>
<td>39</td>
<td>Watt, et al. v. Energy et al.</td>
<td>12/01/81</td>
<td>454 U.S. 151</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>40</td>
<td>North Haven et al. v. Bell, et al.</td>
<td>05/17/82</td>
<td>456 U.S. 512</td>
<td>0.015</td>
</tr>
<tr>
<td></td>
<td>41</td>
<td>State et al. v. Washington Post</td>
<td>05/17/82</td>
<td>456 U.S. 595</td>
<td>0.02</td>
</tr>
<tr>
<td></td>
<td>42</td>
<td>Federal Bureau et al. v. Abramson</td>
<td>05/24/82</td>
<td>456 U.S. 615</td>
<td>0.007</td>
</tr>
<tr>
<td></td>
<td>43</td>
<td>Education, et al. v. Rowley</td>
<td>06/28/82</td>
<td>458 U.S. 176</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>44</td>
<td>Community Tel v. Gotifried et al.</td>
<td>02/22/83</td>
<td>459 U.S. 498</td>
<td>0.006</td>
</tr>
<tr>
<td></td>
<td>47</td>
<td>Trade Commission et al. v. Grolier</td>
<td>06/06/83</td>
<td>462 U.S. 19</td>
<td>0.052</td>
</tr>
<tr>
<td></td>
<td>48</td>
<td>BankAmerica, et al. v. U.S.</td>
<td>06/08/83</td>
<td>462 U.S. 122</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>49</td>
<td>Chappell. v. Wallace et al.</td>
<td>06/13/83</td>
<td>462 U.S. 296</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>51</td>
<td>A.T.F v. Labor Relations et al.</td>
<td>11/29/83</td>
<td>464 U.S. 89</td>
<td>0.048</td>
</tr>
<tr>
<td></td>
<td>52</td>
<td>U.S. v. Weber Aircraft. et al.</td>
<td>03/20/84</td>
<td>465 U.S. 792</td>
<td>0.344</td>
</tr>
<tr>
<td></td>
<td>53</td>
<td>Equal Employment v. Shell</td>
<td>04/02/84</td>
<td>466 U.S. 54</td>
<td></td>
</tr>
<tr>
<td></td>
<td>54</td>
<td>Trans World v. Franklin Mint et al.</td>
<td>04/17/84</td>
<td>466 U.S. 243</td>
<td></td>
</tr>
<tr>
<td></td>
<td>55</td>
<td>Communications et al. v. ITT, et al.</td>
<td>04/30/84</td>
<td>466 U.S. 463</td>
<td></td>
</tr>
</tbody>
</table>

Table 8. Estimated posterior probabilities of regime transitions for the administrative law model \( M_1 \).

We report the structural parameters in Figure 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. The same effect shows for instances when the president can fire an agency head. While the location of the change-point slightly pre-dates *Chevron*, the estimated structural parameters are quite similar. We judge these results to lend some support to the idea that *Chevron* created a jurisprudential regime.
Figure 7. Regime change and probabilities of regime change time series plots for administrative law model $M_1$. 
Figure 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. $N = 1129$. 
5 Conclusion

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

Taken as a whole, what have we learned about jurisprudential regimes from this approach? In the Establishment Clause and administrative law contexts, our results support the conclusions of Kritzer and Richards (2003) that *Lemon* established a regime in the Establishment Clause context, and Richards, Smith and Kritzer (2006) that *Chevron* did in 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 time period study. In search and seizure the model locates the change-point far earlier than hypothesized. One might ask why this is the case. It may be that there is simply too much going on in these cases or that the set of cases is too wide and variable (something surely to be happening in the free speech domain), which means that any empirical model is not comparing likes with likes. Also, the right covariates may not be included in the model. And, of course, it might be that in these areas of the law politics trumps all else and the attitudinalists are correct. This seems to be a plausible explanation in the search and seizure context.

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 decisionmaking 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 doesn’t work in some contexts does not mean we should give up on it. It is implausible that legal considerations do not affect decisionmaking with regard to judgments on the Supreme Court. And even if they did, studying the craft of decisionmaking 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 might not be the best place to look to measure the effects of a jurisprudential regime. Studying the lower courts 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 non-nested 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).

A Model Fitting Using MCMC

We use Markov chain Monte Carlo methods to simulate from the posterior distribution of the parameters of the model. The parameters to be estimated are $Z, \beta_1, \ldots, \beta_K, P, S$. Using the priors

$$p_{ii} \sim \text{Beta}(a, b); \beta_k \sim N(\tilde{\beta}_{0,k}, B_{0,k}),$$

we construct the following recursive sampling scheme to update the parameters:

1. $z_{i,t} | \beta_{x_t}, y_{i,t} \sim TN(x_{i,t}^{\prime} \beta_{x_t}, 1)$, following the data augmentation approach of Albert and Chib (1993)

2. $\beta_\lambda | S, Z \sim N(\tilde{\beta}_\lambda, \bar{B}_\lambda)$, where $\bar{B}_\lambda = (X_{D_\lambda} X_{D_\lambda}^{\prime} + B_{0,\lambda}^{-1})^{-1}$, $\tilde{\beta}_\lambda = \bar{B}_\lambda (X_{D_\lambda}^{\prime} Z_{D_\lambda} + B_{0,\lambda}^{-1} \tilde{\beta}_{0,\lambda})$ and $D_\lambda = \{d : s = \lambda\}$.

3. $p_{ii} | S \sim \text{Beta}(a + n_{ii}, b + 1), i = 1, 2, \ldots, K$, where $n_{ii}$ is the number of one-step transitions from state $i$ to state $i$ in the sequence $S$.

4. To update $S$, we use the algorithm in Chib (1996) and Chib (1998):
   - Define: $s_t = (s_1, s_2, \ldots, s_{t-1}); s^{t+1} = (s_{t+1}, s_{t+2}, \ldots, s_T)$ and $Z_t = (z_1, z_2, \ldots, z_{t-1}); Z^{t+1} = (z_{t+1}, z_{t+2}, \ldots, z_T)$
   - Write the joint distribution as follows:
     $$p(S | Z, \beta, P) = p(s_{T-1} | Z, s_T, \beta, P) \times \cdots \times p(s_i | Z, s^{i+1}, \beta, P) \times \cdots \times p(s_1 | Z, s^2, \beta, P)$$
   - The sampling scheme is:
     $$s_{T-1} : p(s_T | Z, s_n = K + 1, \beta, P)$$
     $$s_{T-2} : p(s_{T-2} | Z, s^{T-1}, \beta, P)$$
     $$\cdots$$
     $$\cdots$$
     $$s_1 : p(s_1 | Z, s^2, \beta, P)$$
• The first state \( s_1 = 1 \) by definition. To implement this sampling, we should know the full conditionals of \( p(s_t|Z, s^{t+1}, \beta, P) \). For this, we can take the following steps:
  - \( p(s_t|Z, s^{t+1}, \beta, P) \propto p(s_t|Z_t, \beta, P)p(s_{t+1}|s_t, P) \)
  - The probability \( p(s_{t+1}|s_t, P) \) is easy to obtain once we have \( P \).
  - Sampling from the filtering density: \( p(s_t|Z_t, \beta, P) \)

\[
p(s_t = k|Z_t, \beta, P) = \frac{p(s_t = k|Z_{t-1}, \beta, P) \times f(z_t|Z_{t-1}, \beta_k)}{\sum_{l=1}^{K} p(s_t = l|Z_{t-1}, \beta, P) \times f(z_t|Z_{t-1}, \beta_l)} \tag{5}
\]

\[
p(s_t = k|Z_{t-1}, \beta, P) = \sum_{l=1}^{K} p(s_t = k|Z_{t-1}, \beta, P) \times f(s_t = l|Z_{t-1}, \beta, P) \tag{6}
\]

* Initialize \( p(s_1 = 1|Z_0, \beta) = 1 \)
* Obtain the mass filtering probabilities \( p(s_t|Z_t, \beta, P) \) by recursively sampling from equation (5) and (6)
* With the mass filtering probabilities in hand, do backward sampling of the states from \( p(s_{T-1}|Z, s^T, \beta, P) \) to \( p(s_1|Z, s^2, \beta, P) \)

### B  Marginal Likelihood Computation using MCMC

We use Markov chain Monte Carlo methods to compute the marginal likelihood for each model. Chib (1995) shows that the marginal likelihood can be expresses as follows:

\[
\log p(Y|\mathcal{M}) = \log f(Y|\mathcal{M}, \beta^*, P^*) + \log \pi(\beta^*, P^*|\mathcal{M})
\]

\[
- \log \pi(\beta^*, P^*|\mathcal{Y}, \mathcal{M}),
\]

where \( \alpha^* \) means that we fix the value of \( \alpha \) at \( \alpha^* \). The likelihood ordinate \( \log f(Y|\beta^*, P^*) \) can be approximated:

\[
p(Y|\beta^*, P^*) = \prod_{t=1}^{T} p(y_t|Y_{t-1}, \beta^*, P^*)
\]

\[
= \sum_{k=1}^{K+1} \Phi(X'_{Dk} \beta_k) Y_{Dk} (1 - \Phi(X'_{Dk} \beta_k))^{1-Y_{Dk}}
\]

\[
\times p(s_t = k|Z, \beta^*, P^*)
\]

\[
\approx \frac{1}{G} \sum_{g=1}^{G} \sum_{k=1}^{K+1} \Phi(X'_{Dk} \beta_k^{(g)}) Y_{Dk} (1 - \Phi(X'_{Dk} \beta_k^{(g)}))^{1-Y_{Dk}}
\]

\[
\times p(s_t^{(g)} = k|\beta^*, P^*, Z^{(g)}).
\]
To do this, we need a reduced run by recursively sampling from \( \pi(S|\beta^*, P^*, Z) \) and \( f(Z|\beta^*, P^*, S) \), and plug the draws of \( S \) and \( Z \) in the above formula.

The posterior ordinate is \( \pi(\beta^*, P^*|Y) = \pi(P^*|Y)\pi(\beta^*|Y, P^*) \) and can be approximated in two steps:

- \( \pi(P^*|Y) \approx \frac{1}{G} \sum_{g=1}^{G} \pi(P^*|S_T^{(g)})\pi(S_T^{(g)}|Y, Z^{(g)}) \)
- \( \pi(\beta^*|Y, P^*) \approx \frac{1}{G} \sum_{g=1}^{G} \pi(\beta^*|S_T^{(g)}, Z^{(g)})p(S_T^{(g)}, Z^{(g)}|Y, P^*) \)

In the second step, we do one reduced run by recursively sampling from: \( \pi(S, \beta|P^*, Z) \) and \( f(Z|P^*, \beta, S) \)

References


