Understanding patterns in medical marijuana laws: a latent class and transition analysis

Hunt, Miles, Boustead

Objective

To compare and synthesize aspects of medical marijuana laws (MMLs) in the United States.

Data Sources/Study Setting

MMLs made effective in 51 jurisdictions, including all 50 states and the District of Columbia, from 1990 to 2012 were compiled from the public law version of state medical marijuana statutes.

Study Design

State laws about access to medical marijuana in 50 U.S. states and the District of Columbia are described for the period 1990–2012. Legislation is compared by year and jurisdiction across provisions of medical marijuana laws.

Data Collection/Extraction Method

Data were extracted from the public law versions of the state statutes and input into spreadsheet format. Mplus 6.11 software was used to perform latent class analysis. STATA 12.0 was used to provide descriptive statistics and perform transition analysis.

Principal Findings

The analysis found that a five-class solution about the legitimacy of medical marijuana adequately described the data: (1) Unacceptable; (2) Research Purposes; (3) Pharmaceutical Framework; (4) Home Remedy; and (5) Mixed Supply. Recently, prevalence in the first four classes has been falling with growth in the Mixed Supply class prevalence. Jurisdictions are statistically more likely to have transitioned from Home Remedy to Mixed Supply than from Unacceptable to Mixed Supply.

Conclusions

The pattern of MML adoption provides interesting insights into the ways laws can develop over time. Jurisdictions tended to initially differ with respect to the legal provisions approved and over time, they appear to be converging. There are a number of reasons why this may occur-changes in the political economy or learning what works from a legal point of view. An important implication, however, is that jurisdictions tend to converge to a legal framework that may be deemed more legally feasible, not necessarily what is optimal from a public safety and health point of view. In which case, it becomes important that public health and safety agencies develop flexible health promotion and diversion monitoring activities relevant to specific legal frameworks.

Keywords: Medical marijuana, legal framework, latent class analysis, drug laws

Abstract:

This paper provides quantitative evidence on the underlying views of voters and state lawmakers about the legitimacy of medical marijuana based on voter- and legislature-adopted statutes between 1990 and 2012. Using latent class analysis and transition analysis, we determine whether state laws reveal underlying beliefs about the legitimacy of medical marijuana and the likelihoods of changing classes. Five distinct classes were identified: (1) Unacceptable; (2) Research Purposes; (3) Pharmaceutical Framework; (4) Home Remedy; and (5) Mixed Supply. Jurisdictions have a statistically greater likelihood of transitioning to a more varied supply framework if they have already passed a ballot initiative with home cultivation supply only and patient-recommended registration. A coordinated and flexible public health and public safety approach is needed to address the relevant legal frameworks adopted over time.

1. Introduction

With an increasing number of U.S. jurisdictions legally permitting the use of medical marijuana, there is increased interest in understanding the pattern by which such legalization has occurred. Since 1996, when California voters passed Proposition 215 allowing marijuana for medicinal purposes, 17 other jurisdictions[1] have also enacted laws permitting marijuana for patients' use by January of 2012. Although much research has focused on the pattern of adopting a medical marijuana law (MML), there may be more legal types than simply the existence of a MML or not. Investigation of legal access to medical marijuana indicates there is a great deal of heterogeneity in the legal provisions comprising a jurisdiction's MML in terms of patient registry requirements, home cultivation restrictions, dispensary supply constraints, and so forth (Pacula et al. forthcoming). Little analysis has been done to understand the types of MMLs and adoption patterns over time, taking into account that jurisdictions have actually approved different sets of legal provisions. As such, questions remain about how many MML types there are, which key provisions distinguish the types, and how likely jurisdictions are to change types over time.

Given the large range of legal provisions in place across jurisdictions, it is useful to synthesize the variation of legal provisions into more manageable, yet distinctive types of MMLs. However, it is challenging to identify the relevant dimensions and build a classification system that can be analyzed over time. While some classifications exist based on observable features of MMLs (Marijuana Policy Project 2011; Mikos 2009), they are founded on authors' subjective opinions about important distinctions. While these classifications may explain some of the variation in legal provisions at a particular point in time, it is not clear if there are statistically unique classes. Furthermore, there may be meaningful underlying relationships that can only be revealed through latent approaches.

To reduce the complexity of the combination of provisions into a smaller set of classes, this study applies latent class analysis (LCA), which detects statistical patterns of association in the legal database and proposes the presence of underlying classes which are able to explain the association. We are not aware of any other study using LCA to understand patterns in law adoption. However, LCA is often used to understand patterns in drug use from large survey data and thus develop targeted prevention and treatment options. One such classification based on LCA identified three classes of illegal opioid users differing in terms of type of drugs co-used, social context and co-morbid pathologies (Monga et al. 2007). In this study, a MML class is characterized by a pattern of conditional probabilities indicating the chance that a jurisdiction adopted legal provisions. We use a database of 22 legal provisions about access to medical marijuana over a 23-year period (1990–2012) across 51 jurisdictions. This is the first study we are aware of that statistically identifies classes of MMLs and analyzes the likelihood of jurisdictions transitioning across classes.

2. Methods

a. Population and study design

We use a database of medical marijuana legal provisions adopted across all 50 states and the District of Columbia (51 jurisdictions) between 1990 and 2012 developed in Pacula et al.

[1] Defined by the 50 U.S. states and District of Columbia.

(forthcoming). Fifteen jurisdictions had therapeutic research statutes in place at some points over the period investigated, which did not allow for “medical use” as described in state laws. Seventeen jurisdictions had a law permitting medical marijuana use made legally effective by January 1, 2012. Pacula et al. (forthcoming) reviewed state statutes to determine if and when jurisdictions had adopted 22 legal provisions of interest.

The legal database includes jurisdictions’ approval or not to provisions across themes related to: the method of enactment, legal protections, types of health conditions covered, process of obtaining medical marijuana and supply mechanisms. Table 5 in the Appendix provides definitions of these statutory laws analyzed. Details of the methodology and statute wordings are published elsewhere (Pacula et al. forthcoming).

b. Statistical analysis

The aim of our analysis was to reduce the complexity of the combination of legal provisions in each jurisdiction into a smaller set of classes. To capture nuances in the text of the law and to ensure all variables are categorical—a necessity of the statistical procedure—we reformulate the 22 legal provisions into 31 binary, categorical variables. In practice, this meant restructuring lists (e.g. of health conditions for which medical marijuana can be used) or descriptions of the nature of a provision (e.g. recommended/required/silent) into variables with ‘yes’ or ‘no’ responses. We used each jurisdiction–year combination as the unit of analysis, giving us 51 jurisdictions by 23 years for a total analytic sample of 1,173 units.

LCA was performed on legal provisions approved and made effective by the beginning of each calendar year across the timeframe 1990–2012. LCA assigns a probability of class membership to each unit of analysis for each class. Each class is then described in terms of the measures (in our case, the probability of “responses” to each of the 31 legal provisions). We test the sensitivity of results to using the enactment, rather than the effective, date of legal provisions. Results provided in the Appendix indicate the number of classes is robust to the date used. Models are estimated with varying numbers of classes, and the best model of fit is identified using the statistical software package Mplus 6.11 (B. O. Muthén and L. Muthén 2011).

We estimated models with one through seven latent classes to determine the best fit. The model of best fit is determined using the Bayesian Information Criterion (BIC; Schwarz 1978) and the Akaike Information Criterion (AIC; Akaike 1985). Once the best model is identified, the pattern of the response probabilities is used to name the categorical latent variable and the classes. We then model both the prevalence of latent class membership and the incidence of transitions over time in observed class membership. To determine transition probabilities, we use the latent class membership in each jurisdiction–year determined in Mplus as a function of previous year class membership and perform logistic regression analysis using Stata.

3. Results

A series of LCA models with one through seven latent classes of MML adoption were run, and for each model, identification was assessed. Table 4 in the Appendix presents model fit information used in selecting the final model of MML classification in the current study. The table includes the AIC and BIC for models with two through seven latent classes. Classes are based on jurisdiction–year combinations; therefore, jurisdictions can belong to different classes over time.

Lower BIC values reflect an optimal balance between model fit and parsimony, and we find a six-class solution has a lower BIC than a seven-class model. Based on these findings, we then narrowed the model choice to the five-class and six-class models by comparing conceptual interpretability. When extracting six classes, one of the classes was split into two based on the item "physicians can prescribe," and the sixth class includes only one jurisdiction. This conceptual distinction was determined to be unimportant, and the change in value of BIC shows little is gained with a sixth class (Table 4). Therefore, we retained the five-class model of MML adoption over time.

a. Prevalence of classes

Results of the LCA, in Table 1, are the probabilities of having provisions in place conditional on class membership. The rows of the table show the reformulated 22 provisions into 31 binary, categorical variables, which are, in turn, presented as subdivided into seven groupings: *aspects of process* (5 variables); *supply mechanisms covered* (8 variables); *affirmative defense* (3 variables); *patient registration* (2 variables); *health conditions explicitly permitted* (7 variables); *type of medical use law* (3 variables); and *enactment of medical use law* (3 variables).

Results of the statistical analysis identify five distinct classes of MMLs: (1) Unacceptable; (2) Research Purposes; (3) Pharmaceutical Framework; (4) Home Remedy; and (5) Mixed Supply. Row one of the table shows the highest prevalence of jurisdiction–years is the "Unacceptable" class (0.53), which maintains a zero probability of adopting any law for medical marijuana.

We label a second class that does not view marijuana as legitimate for patient use as "Research Purposes," because a key feature of the class is the high probability (0.92) that researchers may obtain marijuana for therapeutic research. Furthermore, the probability of explicitly adopting a measure to obtain supply through the National Institute of Drug Abuse (NIDA) is 0.55 within this class. It may be fairly obvious that adoption of therapeutic research statutes and NIDA supply go hand-in-hand because federal regulations stipulate NIDA is the sole supplier of marijuana for research purposes (National Institute of Health 1999). However, it could have been implicitly assumed and, thus, unnecessary to clarify NIDA supply in state law. This suggests there are a number of jurisdictions that consider therapeutic benefit research on marijuana as valid, but for which obtaining a supply for research purposes may be unclear.

Three classes emerge with beliefs that marijuana is legitimate for patient use. They vary, however, on how marijuana can be supplied and for what conditions. We label one class "Pharmaceutical Framework" because this class generally permits physicians to prescribe (0.61), but does not adopt provisions addressing *how* patients can legally acquire and possess medical marijuana. While there is a relatively small probability that these jurisdictions adopt a provision permitting pharmacies to dispense marijuana (0.36), there is no legally viable supply to pharmacies. This indicates the legal provisions adopted resemble that of a pharmaceutical infrastructure, where the legal supply of medical marijuana is not identified.

The two other classes permitting use, on the contrary, adopted provisions that legally permit the supply of medical marijuana. We label one of the classes "Home Remedy" because the collection of provisions adopted indicates marijuana produced at home is always permitted for a limited scope of health conditions such as glaucoma, cancer, HIV/AIDS, and for only narrow drivers of pain (i.e., chronic or debilitating disease or treatment for such diseases that produce severe pain). These jurisdictions indicate patient registration is a recommended, not required, aspect of the legal framework.

The last class permitting use, “Mixed Supply,” has small but nonzero probabilities of adopting provisions to allow dispensaries (0.23) and state distribution (0.47), as well as home cultivation (0.79). This class is also less likely to recommend patient registry than Home Remedy jurisdictions–years, approximately 0.3 and 1.0, respectively, and less likely to only permit the more narrow definition of pain, 0.61 and 1.0, respectively.

Finally, a potentially interesting distinction between classes effectively permitting use for patients—the last two classes—is the method of enactment of legal provisions on medical marijuana. Mixed Supply jurisdiction-years tend to enact legal provisions through legislative voting (0.75), whereas the Home Remedy group has a zero probability of enacting laws through their legislatures. This may be because it is relatively difficult to develop the legal language for a legitimate retail distribution channel for marijuana. It may necessarily require the legislature to be involved in dialogues and in developing the documented legal language to reliably enact a provision permitting patient distribution entities, such as dispensaries, cooperatives, and treatment centers.

Based on findings from LCA, we present key provisions distinguishing classes from each other in Figure 1. Whereas previous research essentially “stopped” after the first issue of whether a state law was passed or not, we illustrate in the figure how taking into account provisions of MMLs generates other statistically and conceptually substantive classes of MMLs. The figure shows there are three particular provisions that further distinguish classes from each other beyond having passed a state law on medical use, particularly therapeutic research law, pharmacy distribution law, and supply mechanisms.

Table 1: Results of Latent Class Analysis of Medical Marijuana Statutory Law Adoption

	Latent Class				
Assigned Label	**Unacceptable**	**Research Purposes**	**Pharmaceutical Framework**	**Home Remedy**	**Mixed Supply**
Proportion of jurisdiction–years	0.53	0.23	0.12	0.03	0.10
Conditional probability of a Yes response					
Aspects of Process					
Physician can prescribe	0.00	0.08	**0.61**	0.19	0.17
Patient/caregiver may obtain recommendation	0.00	0.00	0.36	**1.00**	**0.92**
Health insurers explicitly not liable	0.00	0.00	0.00	**0.70**	**0.76**
Reclassification	0.00	0.00	0.31	0.00	0.18
Researchers may obtain for therapeutic research	0.00	**0.92**	0.00	0.00	0.42
Supply Mechanisms Covered					
NIDA supply	0.00	**0.55**	0.00	0.00	0.13
Home cultivation	0.00	0.00	0.00	**1.00**	**0.79**
Home cultivation requirements	0.00	0.00	0.00	0.10	0.02
Dispensaries	0.00	0.00	0.00	0.10	0.23
Pharmacist authorized to dispense	0.00	0.00	0.36	0.00	0.00
State authorized supply	0.00	0.14	0.00	0.00	0.42
Appropriate means	0.00	0.28	0.00	0.00	0.17
Supply mechanism not addressed	0.00	0.15	**0.99**	0.00	0.02
Affirmative Defense					
Physician	0.00	0.00	0.19	**0.83**	**0.89**
Caregiver	0.00	0.00	0.06	**1.00**	**0.90**
Patient	0.00	0.00	0.00	**1.00**	**0.90**
Patient Registration					
Registration recommended	0.00	0.00	0.00	**1.00**	0.27
Registration required	0.00	0.00	0.00	0.00	0.45
Health Conditions Explicitly Permitted					

Assigned Label	Latent Class Unacceptable	 Research Purposes	 Pharmaceutical Framework	 Home Remedy	 Mixed Supply
Glaucoma	0.00	**0.78**	0.36	**1.00**	**0.93**
Cancer	0.00	**0.89**	0.36	**1.00**	**1.00**
HIV/AIDS	0.00	0.00	0.16	**1.00**	**1.00**
Other	0.00	0.49	0.26	**1.00**	**0.99**
Narrow pain definition	0.00	0.00	0.01	**1.00**	**0.61**
General pain definition	0.00	0.00	0.00	0.00	0.28
Broad pain	0.00	0.00	0.01	0.00	0.14
Type of Medical Use Law					
Statute	0.00	0.00	0.06	**0.70**	**1.00**
Constitutional amendment	0.00	0.00	0.01	0.30	0.00
None	**1.00**	**1.00**	**0.93**	0.00	0.00
Enactment of Medical Use Law					
Legislative	0.00	0.00	0.06	0.00	**0.75**
Ballot	0.00	0.00	0.01	**1.00**	0.25
None	**1.00**	**1.00**	**0.93**	0.00	0.00

Item-response probabilities greater than 0.5 shown in bold to facilitate interpretation.
Note. The probability of a “No” response can be calculated by subtracting the item-response probabilities shown above from 1.

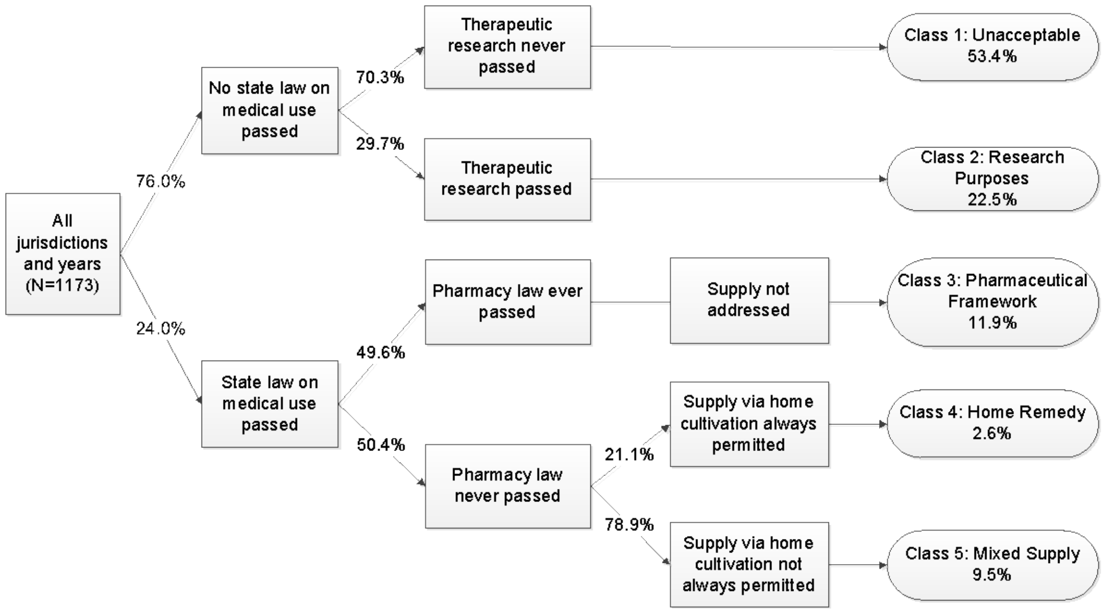

Figure 1: Distribution of statutory laws adopted on medical marijuana for patient use, therapeutic research, home cultivation and pharmacy distribution, 1990–2012

To better understand the size of these classes over time, we plot the prevalence in each class annually in Figure 2. Since 1997, prevalence in classes not permitting medical marijuana has fallen steadily while the Mixed Supply class prevalence has grown steadily over this period. The Home Remedy framework grew in the early 2000s and has plateaued, even falling since 2010.

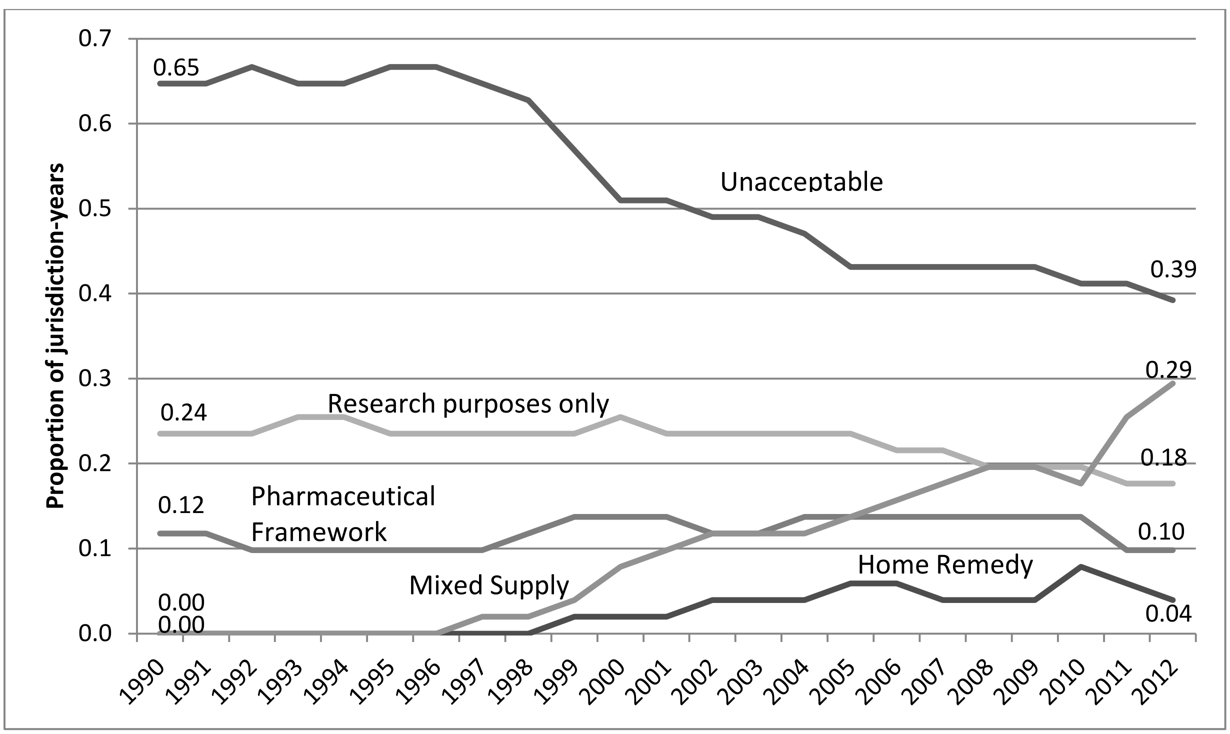

Figure 2: Prevalence by class, 1990–2012

b. Class transitions

Having observed there are changes in the prevalence of classes over time (as shown in Figure 2), we test the hypothesis that particular transitions between classes are more likely. Results presented in Table 2 indicate the average marginal effect of the previous year class on the probability of belonging to the Home Remedy class (column one) and the Mixed Supply (column two) class, because we are most interested in understanding transitions to classes that were effective in legally providing access to medical marijuana.

With a limited time period in which jurisdictions permit both medical use and a viable supply of marijuana, there are few statistically significant findings toward permitting medical use. Nevertheless, evidence indicates there is a statistically greater probability (13 percentage points) of transitioning from Home Remedy to Mixed Supply than from Unacceptable to Mixed Supply. In other words, the pattern observed in Figure 2 for a fall in prevalence of the Unacceptable class and an increase for the Mixed Supply class is not a direct shift. Jurisdictions are more likely to enter the Mixed Supply class via the Home Remedy class. This result indicates the path toward legislative involvement and broader uses of medical marijuana is more likely to occur *after* ballot initiatives with recommended patient registration and home cultivation as the only source of supply are passed.

Table 2: Logistic regression results of transition probabilities

	Marginal effect on probability of membership to class:	
	Home Remedy	**Mixed Supply**
Class at time t-1 (*Unacceptable omitted*)		
Research Purposes	-	0.006
	-	(0.009)
Prescription Without Supply	0.001	0.005
	(0.008)	(0.011)
Home Remedy	0.851***	0.133**
	(0.066)	(0.066)
Mixed Supply	0.004	0.980***
	(0.011)	(0.011)
Observations	866	1,122
R^2	0.64	0.78

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Marginal effects of discrete change from Unacceptable class.

4. Robustness Check

LCA identifies an underlying structure to describe data. As such, the approach can be relatively sensitive to the inclusion and exclusion of data, where adding more covariates in LCA is usually associated with a reduced number of classes. We test the sensitivity of our results by removing a variable. We could have removed any of the legal variables; however, the aim was to identify a variable that we could anticipate the effect of doing so. Upon examination, we determined “supply not addressed” was appropriate, because it is a distinguishing factor for the Pharmaceutical Framework class. If our model is robust, we might expect jurisdiction–years in

Pharmaceutical Framework to split across other classes and few if any other changes. Results presented in the Appendix in Tables 5 and 6 show precisely this result, and findings are robust in terms of the number of classes.

5. Discussion

a. Main results

This study makes several contributions to the literature on the adoption of MMLs. First, we have contributed to the growing literature differentiating MMLs across jurisdictions. Previous studies have initiated efforts to distinguish between various legal frameworks. Based on laws similar to those in this paper, one classifies jurisdictions into seven categories based on the legal certainty of access to medical marijuana (Marijuana Policy Project 2011). Mikos (2009) identifies five categories of jurisdictions with MMLs based on legal protections and state involvement. However, in both of those studies, the classification is subjective, with the authors defining their classifications based on observed characteristics they determined to be conceptually important. This is the first study, to our knowledge, to extend classification of the MMLs into multiple groups based on statistical analysis of underlying relationships in legal data. In jurisdiction–years classified as viewing medical marijuana as Unacceptable (33 jurisdictions in 1990, or 65 percent; 20 by 2012, or 39 percent), the laws prohibit all medical marijuana use and research. The Home Remedy and Mixed Supply classes have similar probabilities of permitting affirmative defenses for physicians, caregivers, and patients but varying probabilities of patients' requirements and supply options. We also identify a Pharmaceutical Framework class and a Research Purposes class for which the probabilities of affirmative defenses were similarly low, but where the likelihood of passing provisions on pharmacies, prescriptions, and research differed.

Second, we characterized patterns of law adoption before and after enacting an MML to assess how jurisdictions progress to permitting marijuana for medical use. We were unable to identify another study that statistically analyzed patterns of adopting MMLs. Even though it may look like jurisdictions transition from legally Unacceptable to a Mixed Supply legal class (based on the pattern shown in Figure 2), our analysis revealed that the probability of transitioning from Home Remedy to Mixed Supply was 13 percentage points greater than transitioning from Unacceptable to Mixed Supply. This means that the progression of legal provisions toward a Mixed Supply class is more likely to occur only after having adopted a Home Remedy legal framework.

Third, sensitivity analysis provides insights into the nature of law adoption over time. Results indicate that jurisdictions began legalization with more unique legal frameworks; however, over time, there appears to have been convergence in MMLs. One reason offered is that jurisdictions perhaps learned from other jurisdictions and started adopting similar language in their laws. Another possibility is that there were changes in the political economy that led to changes in voting behavior. More thorough analysis is needed to test these hypotheses.

b. Limitations

Although this is, to our knowledge, the first study to consider medical marijuana legal frameworks using statutory law data and latent classification techniques, several limitations warrant discussion. First, all legal measures use interpretative law data. That is, RAND (*forthcoming*) developed a set of criteria to determine whether a statute does or does not legally permit an activity. Despite this limitation, the data set was compared to other interpretations and found to be consistent with other widely used sources, such as the National Conference of State Legislatures, thus suggesting reduced reporting bias. Second, MML adoption is recent, which means that the Home Remedy and Mixed Supply groups have low prevalence, 3 percent and 10 percent, respectively (as shown in Table 1 and Figure 1). Consequently, the statistical power to identify transitions out of non-medical use classes is limited. Third, because of the statistical procedure applied, we limit the legal provisions to categorical variables. We do not include provisions such as the number of plants permitted, because they were neither categorical nor normally distributed, which is problematic in mixture models. These provisions may influence the availability of marijuana within a legal framework and, thus, the classes identified. Nevertheless, we capture several availability-related variables shown to be of importance, such as home cultivation and dispensaries (Pacula et al. 2002). In addition, the reader should be cautioned about reification—the classes that emerged are in no sense a "real" set of categories into which jurisdictions can be assigned; rather, they are a description and representation of what was found in the data.

6. Conclusion

While there have been no shortage of opinions about what jurisdictions may be doing by adopting particular sets of legal provisions for medical marijuana, there has been limited statistical evidence. By applying LCA, we statistically identify the types and patterns of MML adoption that were not apparent by simply looking at the numerous variations of medical marijuana laws. LCA appears to be a useful, yet underutilized tool in legal analysis and with wider application, there may be more we can uncover about the development of other laws, such as civil rights, firearm controls, and many more. Although it is not possible from this type of analysis to conclude why particular patterns were observed, the pattern of convergence we identify raises important questions as to why jurisdictions are converging to this particular legal framework and whether it is optimal in terms of other socio-economic outcomes, such as economic, health and safety.

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7. **Appendix**

Table 3: Variable descriptions

Theme	**Variable**	**Description**
Form and formation of law	Law type for medical use	Law was statutorily enacted Law was created by a constitutional amendment
	Enactment type for medical use	Law was passed by legislature Law was passed by a voter-initiated ballot
	Therapeutic research	Statute only allows medical marijuana to be used in a research setting or in clinical trial, not to be used by patients who are not participating in medical research
	Reclassification	Law explicitly contains a provision reclassifying medical marijuana
Legal protection	Physician affirm	Law explicitly allows physicians to use an affirmative defense if they face charges because they recommend (prescription, authorization) medical marijuana to a patient
	Patient affirm	Law allows medical use as any type of affirmative defense to at least one type of marijuana crime under any situation
	Caregiver affirm	Law allows medical use an any type of affirmative defense to at least one type of marijuana crime under any situation
	Patient protect	Some form of legal protection is provided for patients who obtain medical marijuana upon the recommendation/ authorization of a physician
Health conditions	<condition>	Law specifically states that medical marijuana can be used to treat <condition> (e.g.: if the law lists <condition> as an allowable medical condition). Conditions explicitly considered are: glaucoma, cancer, HIV/AIDS. Note that pain is brought out as another variable definition because of less objective measurement
	Pain1, pain2, pain3	**Pain1:** Medical marijuana can be used if the patient has a disease that causes pain (e.g.: "a chronic or debilitating disease or treatment for such diseases, which produces severe pain") **Pain2:** Medical marijuana can be used to treat pain, without requiring that the pain is caused by a medical condition (e.g.: a definition of debilitating medical condition that includes intractable pain) **Pain3:** Medical marijuana can be used provided a physician determines it is medically justified (e.g.: a statute that allows medical marijuana to be used "in the treatment of any other illness for which marijuana provides relief")
Process	Patient registry	Law explicitly requires patient participation in the system or does not provide for any legal protection for patients who do not participate in the registry system
	Health insurance	Law explicitly states insurers are not liable for claims

Theme	Variable	Description
		associated with medical marijuana
	Pharmacy provide	Law explicitly contains a provision allowing patients to obtain medical marijuana from a pharmacist
	Physician prescribe	Law explicitly indicates a physician can “prescribe” medical marijuana
Supply mechanisms	NIDA supply	Law explicitly allows patients to obtain medical marijuana from the National Institute on Drug Abuse
	Home supply	Law either: (1) includes an explicit statement allowing for home cultivation, (2) defines medical use to include cultivation, or (3) includes a particular number of plants in describing use
	Dispensary supply	Law explicitly states dispensaries (or equivalent organizations) are permitted
	Law enforce supply	Law explicitly allows patients to obtain medical marijuana from law enforcement sources
	Most appropriate supply	Law explicitly states that patients are allowed to obtain marijuana for medical use by the means most appropriate
	Non-addressed supply	Law does not include any discussion of how medical marijuana users are able to obtain marijuana for medical use

Table 4: Model fit information used in selecting the LCA model

Number of Latent Statuses	AIC	BIC
3	11211.9	11693.3
4	10712.0	11355.6
5	**9950.5**	**10756.2**
6	9520.9	10488.8
7	9362.0	10492.0

Note: Bold entries reflect selected model.

Robustness

Model-of-fit statistics indicate a similar structure to original results in terms of the number of classes (e.g., a five-class solution). Results in Table 5 show that the Pharmaceutical Framework class separates into several classes, because a defining characteristic of the class was that jurisdictions did not address the supply mechanism for patients yet adopted laws on protections for pharmacists and prescribing physicians. This sensitivity analysis indicates the importance of including the weakness of state laws to “not address supply.”

Table 5: Sensitivity analysis removing unaddressed supply

Alternative data classification / Original classification	**Unacceptable**	**Research Purposes**	**Pharmaceutical Framework**	**Home Cultivation**	**Mixed Supply**
1	0	0	1	30	112
2	0	21	50	0	0
3	0	244	0	0	0
4	0	0	45	0	0
5	626	0	44	0	0

Model-of-fit results similarly indicate a five-class solution, as we saw in original findings. In terms of the type of classifications, a cross-tabulation of the new classification with the original classification indicates some shifting, as shown in Table 6. By allowing MMLs to be in place for a greater period of time, there is less of a distinction between Home Remedy and Mixed Supply, which are now grouped together with some jurisdiction–years previously classified as Unacceptable (class=1). This change essentially groups together jurisdictions that eventually permit medical marijuana through any supply mechanism. Another interesting result is that jurisdictions previously identified as being in the Pharmaceutical Framework class are split into two separate classes when using enactment dates, with one class essentially only including those jurisdiction–years with a Pharmaceutical Framework (class=3) and another class combining research therapeutic law adoption with pharmaceutical law adoption (class=4).

Table 6: Sensitivity analysis using enactment dates

Enactment date classification / Original classification	**Unacceptable**	**Research Purposes**	**Pharmaceutical Framework**	**Home Remedy**	**Mixed Supply**
1	13	3	2	30	110
2	2	0	72	0	2
3	0	244	0	0	0
4	2	16	66	0	0
5	609	2	0	0	0