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A typology of prescription drug monitoring programs: A latent transition analysis of the evolution of programs from 1999 to 2016

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Abstract

Aims/Background—Prescription drug monitoring programs (PDMP), defined as state-level databases used in the USA that collect prescribing information when controlled substances are dispensed, have varied substantially between states and over time. Little is known about the combinations of PDMP features that, collectively, may produce the greatest impact on prescribing and overdose.

Methods—Our study used latent transition analysis to: (1) identify the types of PDMP models that have developed from 1999 to 2016; (2) estimate whether states have transitioned across PDMP models over time; and (3) examine whether states have adopted different types of PDMP models in response to the burden of opioid overdose.

Results—We divided the time period into three intervals (1999–2004,2005–2009,2010–2016), and found three distinct PDMP classes in each interval. The classes in the first and second interval can be characterized as “No/Weak”, “Proactive”, and “Reactive” types of PDMPs, and in the third interval as “Weak”, “Cooperative”, and “Proactive”. The meaning of these classes changed over time: until 2009, states in the “No/Weak” class had no active PDMP, whereas states in the “Proactive” class were more likely to proactively provide unsolicited information to PDMP users, provide open access to law enforcement, and require more frequent data reporting than states in the “Reactive” class. In 2010–2016, the “Weak” class resembled the “Reactive” class in previous intervals. States in the “Cooperative” class in 2010–2016 were less likely than states in the “Proactive” class to proactively provide unsolicited reports, or to provide open access to law

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enforcement; however, they were more likely than those in the “Proactive” class to share PDMP data with other states, and to report more federal drug schedules.

Conclusions—Over the 17 years of follow-up, states tended to transition to more robust PDMP classes. Opioid overdose deaths in prior years predicted the state’s PDMP class but did not predict transitions between PDMP classes over time. This study offers an empirical approach to classify PDMP models across states and over time, so that we may identify the impact of different types of co-occurring PDMP features on opioid-related harm.

Keywords

Prescription Drug Monitoring Programs; opioids; latent class analysis; latent transition analysis; prescribing; opioid overdose

INTRODUCTION

At least 190,000 people died worldwide from drug-related causes in 2015 – most of these deaths were opioid related; in the same year, almost 12 million disability-adjusted life years, or 70% of the global burden of disease attributable to drug use disorders, were attributable to opioids[1]. While some of these opioids are beneficial, the unnecessary prescription of opioids is associated with numerous harms, up to and including death. The global crisis of opioid-related harm is especially severe in the United States[2], where opioid related overdose deaths have more than quadrupled from 1999 (3 deaths per 100,000) to 2016 (13.3 deaths per 100,000)[3]. However, opioid overdose rates are increasing globally, as opioids are increasingly used to treat chronic non-cancer pain[4, 5]. As governments and health organizations globally leverage resources to reduce opioid-related harm, it is important to consider the successes and failures of opioid-related policy worldwide.

Prescription drug monitoring programs (PDMPs) constitute one important policy response to the opioid epidemic in the United States. PDMPs are databases that collect information when certain controlled drugs, such as prescription opioids (POs), anxiolytics, or stimulants are dispensed. These data are transmitted to a central location where, depending on state specific PDMP legislation, authorized users such as prescribers, pharmacists and law enforcement officials may access the data[6].

Although studies have shown that PDMP enactment may improve prescribing behavior[7–9], findings have been mixed regarding the association of PDMP enactment with PO overdose. A number of studies found PDMP implementation to be associated with a decrease in PO overdoses[9–15], whereas others found that new PDMP legislation had no effect on statewide PO abuse or overdose[16–18], and others found an association between PDMP enactment and an increase in overall drug overdose death[17, 19].

There are at least four factors that may contribute to discrepant findings on the impact of PDMPs on opioid overdose. First, most early studies treated the presence of the PDMP as a binary variable, without accounting for the substantial variability in PDMP characteristics and implementation that exists across states. Second, PDMPs have changed over time, so that in the same state, a state’s PDMP in 1999 may look quite different than the same state’s

PDMP in 2016. Yet most studies do not account for the heterogeneity in PDMPs within states over time. Third, sets of individual PDMP features are likely to be implemented together. Hence, recent findings on the influence of single PDMP characteristics on prescribing and overdose[20–22] are likely to conflate the effects of clusters of PDMP features adopted by the same states at the same time. This latter phenomenon has led some investigators to create scores of the "robustness" of PDMPs[23], which rely on subjective criteria to assign weights to different PDMP characteristics in the "robustness" score[23]. Fourth, the decision to enact more robust PDMPs is likely not random, but may instead be motivated by the presence of a significant opioid prescribing and/or overdose problem in the state. Such a source of endogeneity needs to be understood and accounted for in evaluations of the impact of PDMPs on opioid-related harm.

We attempted to address these limitations by using an empirical approach—latent transition analysis—to classify states' PDMPs into latent classes that reflect *combinations* of PDMP features that are likely to be adopted together. Identifying latent classes among states reduces complex state-level response patterns into simpler latent PDMP models that may produce distinct effects on opioid-related harm. By adopting a latent transition analysis (LTA) approach, we also documented the progression of PDMP models over time within states, and examined how prior burden of opioid overdose was associated with a transition to more robust PDMP models within states.

Our study had three goals: (1) to use an empirical approach to identify groupings of states with similar PDMP characteristics; (2) to determine the extent to which states have transitioned between PDMP models over time; and (3) to examine whether prior rates of opioid overdose deaths have contributed to a shift in PDMP approaches within states over time.

METHODS

Population and study design

Characteristics of PDMPs enacted in 51 jurisdictions, including 50 U.S. states and the District of Columbia, from 1999 to 2016, were selected and compiled from the Prescription Drug Abuse Policy System (PDAPS) databases of legal provisions[24]. Provisions were compared by year and jurisdiction.

To parsimoniously represent key aspects of PDMP types, we considered nine PDMP characteristics that have been classified by prescription opioid policy experts as potentially important determinants of prescribing practices and prescription opioid overdose events[9, 13, 16, 17, 20, 21, 25]. Some provisions listed as individual questions in the PDAPS databases were adapted into multiple items for our analysis where relevant. Other provisions with more than four response options were reduced into categorical items with a maximum of three response options. The items were adapted not only to facilitate the latent transition analysis (LTA) analysis, but also because preliminary analyses on the un-adapted items suggested that the modifications improved the interpretation of results. The original PDAPS provisions, as well as the original response options are included below in Table 1; in

addition to the exact wording of each question in PDAPS database, Table 1 also includes a comparison of the coding used in our analysis to that of the original data.

The Centers for Disease Control Wide-Ranging Online Data for Epidemiologic Research (WONDER) Database provided mortality data for opioid-related overdose deaths from death certificates filed in the United States from 1999 to 2016[26]. We extracted all deaths attributable to prescription opioid poisonings (ICD-10 codes T40.2-T40.4), including all manners of death (i.e., unintentional, self-harm, assault and undetermined intent). Raw counts were converted to age-adjusted rates for each state and each year.

Analysis

The aim of the analysis was to reduce the complexity of provisions that characterize PDMPs, and to classify states into different types of PDMP classes. Latent transition analysis (LTA) is a type of mixture model and a longitudinal extension of latent class analysis (LCA)[27, 28]. The LTA links the measurement model of an LCA at a discrete time point to subsequent time points through the use of transitional probabilities: these probabilities describe the likelihood of transition between class memberships at each time point[29].

First, we conducted exploratory LCAs to generate estimates of how class membership changed over time, and also how many classes were optimal at each time point[29, 30]. We fit LCA models with one through five classes. The model of best fit was determined using the parametric bootstrapped likelihood ratio test (PBLRT) at alpha = 0.05. The PBLRT uses resampling techniques to test the hypothesis that the log likelihood for a tested (K) class solution is significantly smaller than the log likelihood for a model with an additional (K+1) class[31]. The difference in the likelihood ratio statistic from the empirical data is used to generate random samples where the K class solution is true, but that then is tested against both K and K+1 hypotheses to create a distribution of likelihood ratio statistics for when the K class solution is true. The original observed likelihood ratio statistic is then compared to this distribution.

Second, we conducted an LTA to examine the probability of states transitioning between latent classes at each linked time point. It was not computationally feasible to fit a latent transition model across the entire time period, and furthermore fitting one model for all 17 years would have required us to only use PDMP provisions that were present for all 17 years, which would have prevented us from examining some of the newer PDMP provisions that were present only in later years. We divided the time span into three smaller sub-intervals (1999–2004,2005–2009, 2010–2016) that would avoid sparsity issues in the response pattern matrix, but that also lined up with important historical events. Specifically, these three periods reflect three different periods in the opioid epidemic in the US. The first period represents the “electronic era” of PDMPs, when the first online PDMPs were enacted[32], and the first period of increase in opioid overdoses, driven primarily by prescription opioids[33]. In the second period, US federal funding for PDMPs through sources such as the Bureau of Justice Assistance and by the CDC increased substantially, including through the Harold Rogers Prescription Drug Monitoring Program[34], and in 2005 the National All Schedules Prescription Electronic Reporting Act (NASPER), which

authorized US federal agencies to fund new PDMPs and enhance existing programs [35]. The third period represents two major shifts: first, PDMPs started to expand in this period, with increased adoption of features such as interstate data sharing, real time data collection, unsolicited reports, and integration into standard of care[36], among others. Second, prescription opioid overdose rates stabilized, while heroin overdoses[3], and synthetic opioid overdoses increased (in 2010 and 2013, respectively)[33]. As a result, the latent classes are defined separately for each interval, and although related, are not directly equivalent across intervals[37].

As a follow-up to the LTA we conducted several sensitivity analyses to verify that class composition and item endorsement was not interval specific and to demonstrate that varying the start or end date of the three intervals did not significantly affect interpretation. The additional intervals tested include: 2000–2005, 2001–2006, 2006–2010, 2007–2011, 2011–2016, 2012–2016. Results are presented in tables S3–S5 in the online supplement and show that our results are not unique to the specific start and end dates we selected for our analyses. We did notice—especially in the case of the modified intervals periods of the final interval—that decreasing the variability of an interval by excluding years where a large change took place (e.g. 2009–2012) was the factor that most affected class interpretation in the shortened intervals.

Finally, the flexibility of the LTA model allowed us to examine the association between time-fixed/time-varying covariates and class membership [38]. Specifically, we used opioid overdose rate as a time-varying covariate to predict both latent class at the first time point of each interval (1999, 2005, 2010), and subsequent transition between classes. Overdose rates were age-adjusted and lagged one year. All analyses were conducted in SAS® using the PROC LCA and PROC LTA procedures[39, 40].

RESULTS

The exploratory LCA suggested that the three-class solution presented the optimal fit to the PDMP provision data for eleven out of seventeen of the study years, with four-class solutions for the remaining six (see Table S1). Although not presented in these results, up to five classes were tested in preliminary analyses and were never preferred over the four-class solutions. Hence, we chose a three-class solution with partial measurement invariance as the structure for the LTA analysis. Although the composition of classes differs across waves, the pattern of PDMP characteristics within each class was most comparable in the first two intervals. We therefore used the same labels for class in intervals 1 (1999–2004) and 2 (2005–2009) where classes in each interval are defined as (1) “No/Weak”, (2) “Reactive”, and (3) “Proactive”. The third interval (2010–2016) introduced two additional variables not available in earlier years, and the three-class solution produced classes that were categorically different than those in the earlier intervals. The class labels are defined in the third interval as (1) “Weak”, (2) “Cooperative”, and (3), “Proactive”.

The main findings from the LTA analyses for the intervals 1999–2004, 2005–2009, and 2010–2016 are included in Figures 1 2, and 3, and Table 2. The results of interest include: 1) item endorsement probabilities, which are the basis for class assignment and show the

probability of endorsing a response option given membership in a specific class (Table 2); 2) class proportions, which show the proportion of states assigned to a class per year (Figures 1); and (3) latent transition probabilities, which refer to the probability of transitioning from any class to one of the 2 other classes at the next time point (Figure 2). Only one item endorsement probability is displayed per interval because the partial measurement invariance assumption constrains the endorsement probabilities to be equal at each time point in the interval. As an example, consider provision # 1 "Proactive reports to law enforcement." This provision appears twice in Table 2, as there are two possible response options: (1) No, does not provide proactive reports, or (2) Yes, does provide proactive reports. The item endorsement probability shows, for each class in each interval, the probability of endorsing a response option given membership in a specific class. A probability of 1 means that every state in that class endorsed that response option. Thus, classes are interpreted based on their likelihood of endorsing specific response options. Proportions are reported when referring to class membership at each year, and probabilities are used when referring to item endorsement probabilities for provisions associated with specific intervals. We have also included a panel of maps that show class membership in the first and last year of each interval, to illustrate transitions at the individual state level.

First Interval: 1999–2004

The first interval spanned 6 years and 7 variables. In this interval, states in the "No/Weak" class did not have active PDMPs. The distinction between the "Reactive" and "Proactive" class was that states in the "Proactive" class were more likely to require proactive reporting to law enforcement, prescribers, and dispensers (Table 2), and were more likely to allow open access to law enforcement and require more frequent reporting practices. The "No/Weak" class contained approximately 75% of the total states in 1999, but this dropped to 61% by 2004 (Figure 1). All the transitions occurred out of the "No/Weak" class, with 10% of states transitioning from "No/Weak" to "Reactive" (e.g., Illinois in 2000 or Tennessee in 2002), and 5% of states transitioning from "No/Weak" to "Proactive" (Figure 2) (e.g., Idaho in 2000). The states that did shift classes represent a small cadre of states that adopted PDMP legislation for the first time in this interval, which explains why most transitions were into the less comprehensive "Reactive" class.

Second Interval: 2005–2009

The second interval spanned 5 years and 7 variables. Although this time span allowed for a new PDMP provision (indicating whether a state can share PDMP data with other states), the variable was ultimately excluded from the analysis due to extreme sparseness in response options in this period (the number of states adopting this provision in the years 2005–2009 were 1, 3, 4, 7, and 7, respectively). In this interval, as in the first interval, the "No/Weak" class includes states with minimal to no PDMP legislation. The primary distinction between the "Reactive" and "Proactive" class in the second interval was that states in the "Proactive" class were more likely to require proactive reporting to law enforcement, prescribers and dispensers (Table 2). "Proactive" states, like California or Maine, also continued to be more likely (probability = 0.25 vs. 0.14) to allow open access to law enforcement and require more frequent reporting to the PDMP by users. State membership in the "No/Weak" class decreased across the interval from approximately 55% of the total states in 2005 to less than

30% in 2009 (Figure 1). More transitions were observed during this period (Figure 2). As in the first interval, the majority of transitions occurred from the “No/Weak” class to the “Reactive” and “Proactive” classes.

Third Interval: 2010–2016

The third interval spans 7 years and 9 variables. In this interval, the “Weak” class no longer only contained states with no PDMP legislation, and more closely resembled the “Reactive” class in previous intervals (Table 2). States in the “Cooperative” class in this interval were less likely than states in the “Proactive” (probability = 0.811 vs. 0.487) to require proactive reporting, or open access to law enforcement. All the states in the “Cooperative” class allowed PDMP information to be shared with other states and were more likely to require more frequent reporting to the PDMP (probability = 0.866 vs. 0.810), and to monitor more federal drug schedules than the “Proactive” class (probability = 1.000 vs. 0.232). The “Weak” Class contained about 60% of the states in 2010 but dropped to around 20% by 2016 (Figure 1), whereas the “Cooperative” and “Proactive” classes accounted for approximately the same proportion of states in this interval. Figure 2 shows that transitions between classes during this final interval were the most frequent, and unlike previous intervals, included several instances of transition between the “Cooperative” and “Proactive” classes, such as in the case of Louisiana, which transitioned from “Cooperative” to “Proactive” in 2016. States that move between “Cooperative” and “Proactive” designations are likely adjusting their PDMP legislation to address state specific needs.

Relationship between PDMP class membership and opioid overdose burden

The “No/Weak” or “Weak” class in all intervals was set as the reference group for odds ratio comparisons, as almost all transitions between classes occurred from the “No/Weak” or “Weak” group to either the “Reactive/Cooperative” or “Proactive” class for each interval. In the first two intervals, the logistic regression coefficients relating class membership at the first year of the interval to overdose death in the previous year were highly significant, suggesting that age-adjusted PO overdose rate in the previous year was predictive of latent class membership in both 1999 (OR=1.17; $p<0.001$) and 2005 (OR=1.16; $p<0.001$, see Table 3). Prescription opioid overdose rates in 2009 were not significantly predictive of class membership in 2010 (OR= 1.02, $p = 0.6233$, see Table 3). The p value for each set of odds ratios reflects an omnibus test, which suggests at least one odds ratio is significant. A higher rate of overdose death in the preceding year (1998,2004) was significantly predictive of membership in the “Proactive” class for both the first and second interval.

Table S2 in the online supplement shows odds ratios linking lagged overdose rates to transitions between classes in subsequent years. Transitions between classes were rare in the first interval and were not predicted by prior PO overdose rates, whereas in the second and third intervals, transitions between classes increased but the lagged PO overdose rate continued to not be predictive of transitions between latent classes in the following year.

DISCUSSION

We conducted a latent transition analysis of PDMP characteristics across the 50 United States. Our results support extending state-level PDMP codification beyond a binary classification to a three-level classification. In particular, we found two substantively different patterns in state PDMP policies in more recent years: one in which states have more frequent PDMP reporting requirements, report a larger number of drug schedules, and share PDMP data with other states (a “cooperative” PDMP), and another where PDMPs are required to proactively report suspicious prescribing and dispensing patterns, and provide open access of data to law enforcement (a “proactive” PDMP). The decision to adopt more comprehensive PDMPs appears to be related to prior levels of opioid overdose.

Prior studies that have evaluated the effectiveness of PDMPs have considered a variety of methods to classify state level differences, including a binary classification system (PDMP present/PDMP not present), researcher weighted scores [23], and examinations of specific PDMP policies. Our novel contribution to this area of research includes the use of a data-driven approach to classify states according to their tendency to simultaneously adopt multiple and correlated PDMP policies, and the identification of three distinct types of PDMP models that have evolved in character over time. Future studies can use this classification to distinguish the combinations of PDMP provisions that are most effective in reducing PO related harm.

Our analyses suggest that PDMP classification should be considered relative to the years being evaluated, given that the nature of state level PDMPs changed over the 1999–2016 time period. In the first two intervals, the “No/Weak” class contained only states with no operational PDMP, whereas in the third interval, the endorsement probabilities for the “Weak” class suggested that states with relatively basic PDMPs in later years were more similar to “Reactive” and “Proactive” classes in the first interval. Further, in the first two intervals, the “Proactive” class included states with clearly more robust PDMPs than the “Reactive” class, while in the third interval, the “Cooperative” and “Proactive” classes both reflected robust PDMPs that differed in policies related to proactive reporting, interstate data sharing, access of data for law enforcement, and number of drug schedules reported, but were fairly similar in other features. These findings suggest that studies that examined the relationship between PDMP enactment and overdose during this time period, but did not account for the variable nature of PDMP composition in different segments over time, may have reported artifactually null results. Accounting for variation in PDMP policies over time is thus an important study design consideration when conducting state-level PDMP policy research.

Within each interval most transitions occurred from the “No/Weak” or “Weak” class to one of the other two classes. This overall trend likely reflects the historical tendency for states to expand the capacity of their PDMPs, rather than to make them more restrictive. As noted earlier, US federal support for these programs encouraged expansion. These changes, as measured by transitional probabilities, however, were not significantly predicted by overdose deaths in the preceding year.

Our study findings suggest that part of the state level impetus to implement more comprehensive PDMPs came from exacerbated PO overdose rates in preceding years. In the first and second intervals, state PO-related overdose death rates in the previous year were significantly predictive of class membership in the first year of their respective interval. If specific periods of increased PO-related overdose burden drives increased PDMP legislation, effects of PDMP provisions should be estimated using more complex analytic techniques, such as g-computation[41], or targeted maximum likelihood estimation[42], since prior PO overdose rates may be a confounder of both PDMP characteristics and population-level outcomes. It should be noted that lagged overdose death was used to predict class membership at the first time point in each interval, as well as the probability of transitioning between classes at subsequent time points within each interval. In the first case, our significant results suggest that states with higher rates of overdose death were more likely to implement more comprehensive PDMP policies. However, in the second case, our non-significant results suggest that rates of overdose death do not predict whether a state will transition into a different class within a 5-year interval.

Study findings should be considered in light of the following limitations. First, due to the restricted number of study jurisdictions (n=51 states) and the change in the types of PDMP provisions adopted over time, we had to restrict endorsement probabilities within intervals and divide the 17-year study period into three intervals. Second, state specific PMDP features such as “state sharing of data” or “prescribers must access PDMP” were not enacted in any states until 2005, and 2010 respectively. Latent transition analysis requires heterogeneity in responses for all considered variables, which limited the provisions we could include in each interval to those variables with sufficient heterogeneity. The provisions that differentiated classes in later years were different from those in early years because of the gradual harmonization of PDMPs across states and years. Third, the SAS procedure (PROC LTA) we used to compute odds ratios does not generate standard errors or confidence intervals for individual odds ratios; the p values reported are computed for the covariate as whole, and do not address individual odds. A special characteristic of our data, however, is that our analysis considers all possible measurement units, or states, and so error due to sampling should not affect our estimates. Fourth, PROC LTA did not allow for the prediction of class membership at any other time than the first year in each interval. Future research could use some of the moving windows we tested in our sensitivity analyses to examine the association between predictors such as opioid overdose and PDMP class membership at different time periods.

Our study’s limitations are offset by numerous strengths. First, our study predicts three distinct and stable classes for each interval, representing a significant reduction in dimensionality in the features of PDMPs. Second, latent class techniques allow us to simultaneously consider multiple relevant PDMP provisions. Third, our data include no missing values and are population level data, which allow our classifications to be more descriptive than inferential, at least within the considered interval.

In conclusion, our findings show that a binary classification system for state PDMPs fails to capture true heterogeneity across states and over time. We identified three latent classes of PDMPs in each of the intervals 1999–2004, 2005–2009, and 2010–2016. Our results suggest

that states can be grouped into meaningful and separate classes that are distinct from each other based on a combination of co-occurring features, rather than any one isolated characteristic. If certain combinations of PDMP provisions are more effective at reducing overdose death than others, grouping states with similar provisions together may help to identify those combinations. Transitions between classes occur incrementally rather than gradually, and an overall trend of states transitioning into classes with more comprehensive PDMP legislation is observed across all intervals. While this trend is not surprising, it does imply that latent classification is more meaningful when conducted at smaller intervals, as it facilitates the interpretation of endorsement probabilities, and allows for models to be fit during distinct time periods when latent classes mean the same thing in each year. In sum, latent transition analysis may prove a pivotal tool for future PDMP research.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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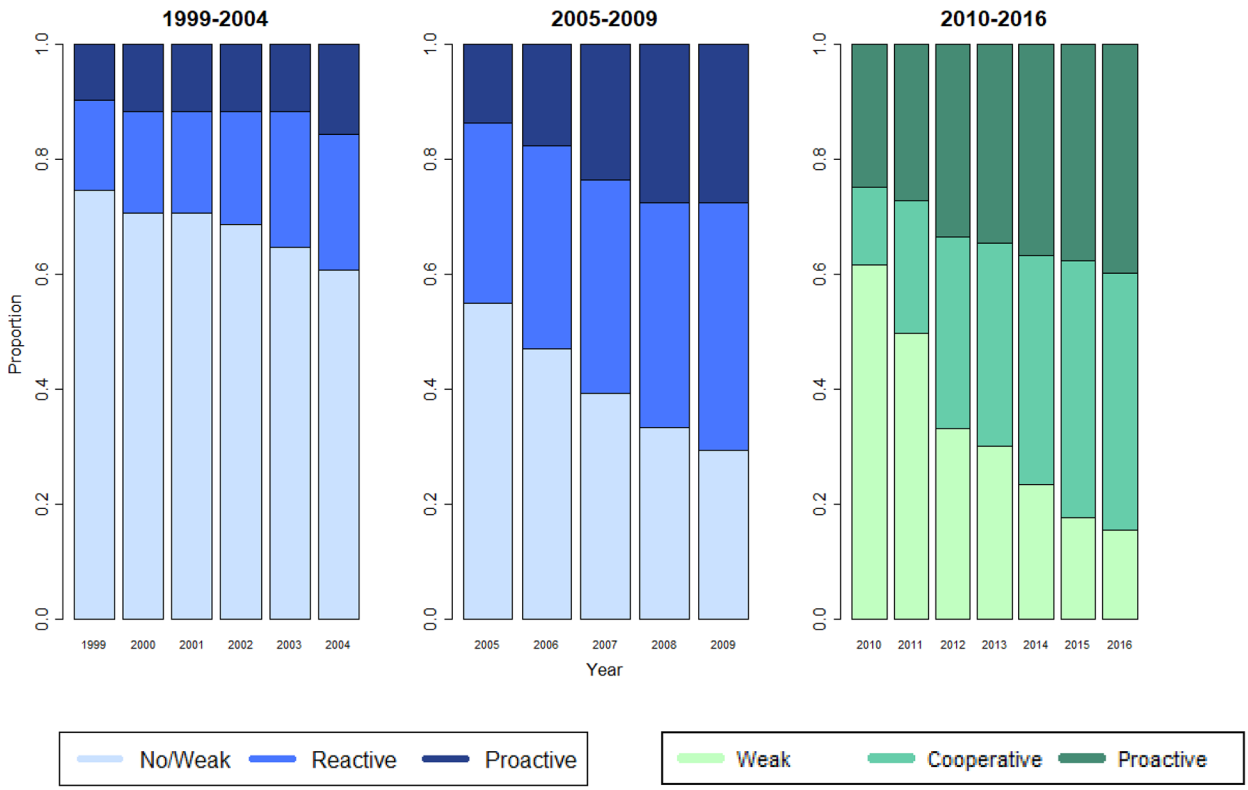

Figure 1:
PDMP class membership proportions by year and interval, 1999–2016

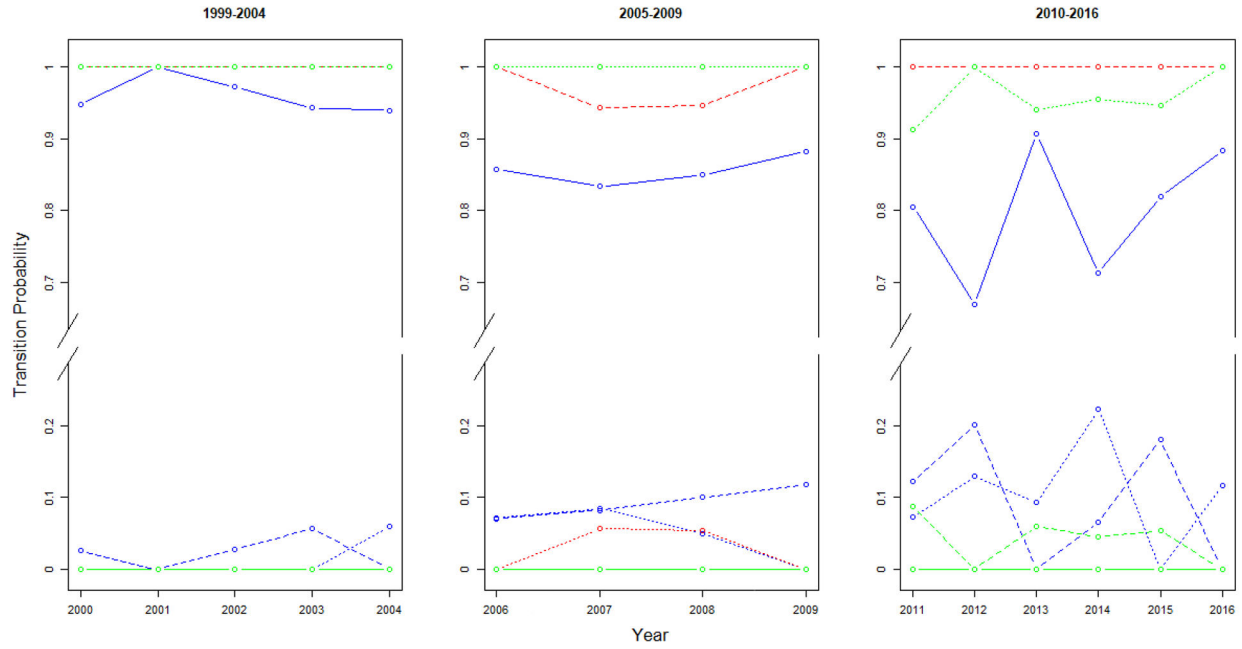

Figure 2:

Transition Probabilties in each interval, 1999–2016

Note: Each point denotes the probability of transitioning into a given class, given membership in a given class in the previous year. Some lines are not visible as some probabilities are identical across years and the lines lie on top of each other. For a full description of transitional probabilities, please refer to table S6.

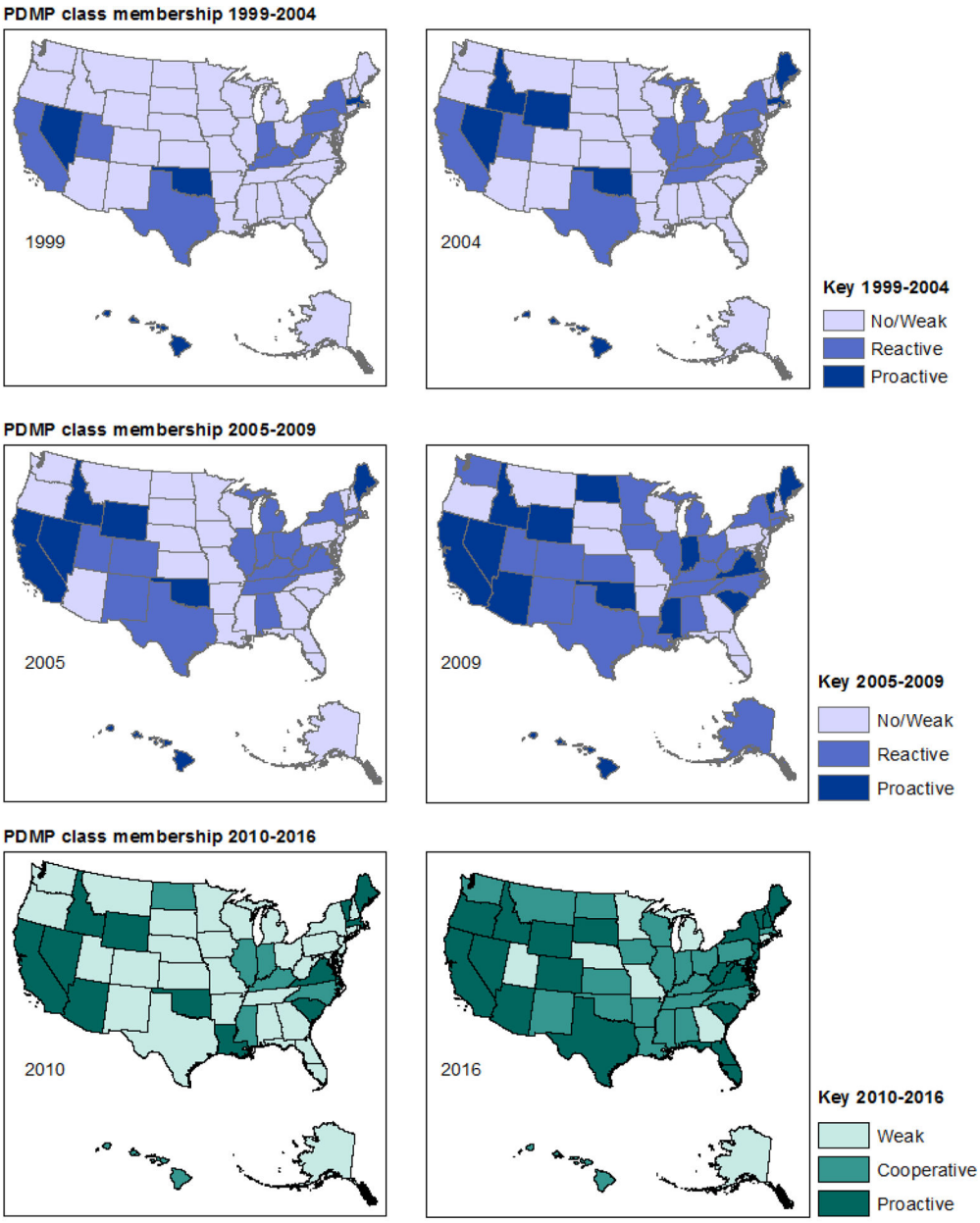

Figure 3:
Latent class membership by state and year

Table 1:

Original provisions of prescription drug monitoring systems, provided by the Prescription Drug Abuse Policy System*

Variable	Original PDAPS variable description	Years Available
1	Required OR permitted to report to law enforcement	1999–2016
2	Required OR permitted to report to professional licensing body	1999–2016
3	Required OR permitted to report to prescriber or dispenser	1999–2016
4	What drug schedules are required to be reported to the PDMP?	1999–2016
5	How often must dispensers report data to the PDMP?	1999–2016
6	For what purpose does the law allow in-state law enforcement to access PDMP data?	1999–2016
7	Whose PDMP data does the law allow prescribers to access?	1999–2016
8	Does the law permit the PDMP to share data with other state PDMPs?	2005–2016
9	Does the state require prescribers to check PDMP when prescribing?	2010–2016
Variable	**Original PDAPS response options**	**Collapsed response options for LTA**
1	0=no; 1=yes	0=no; 1=yes
2	0=no; 1=yes	0=no; 1=yes
3	0=no; 1=yes	0=no; 1=yes
4	0=No report (or pre-enactment); 1=Federal schedule I; 2 = Federal schedule II, III; 3=Federal schedule II, III, IV; 4=Federal schedule II, III, IV, V; 5=Federal schedule I, II, III, IV, V	0=no reporting; 1=Any Federal schedules II-V, 2=All federal schedules I-V
5	0=No reporting (or pre-enactment); 1=No time specified (or other); 2=Every 28 days or more; 3=Between 8 and 27 days; 4=Every 7 days; 5=Between 2 and 6 days; 6=Every day; 7=Real-time	0=no reporting; 1= Reporting required every 8 days-no time unspecified; 2=Reporting required at least weekly
6	0=pre-enactment; 1=No access; 2=access with subpoena or warrant; 3=access with active investigation; 4=access with no restrictions	0=no access; 1=access with subpoena, warrant, or active investigation; 2=access with no restrictions
7	0=no access; 1=patient access, 2=prescriber access	0=no access; 2= patient and prescriber access
8	0=no; 1=yes	0=no; 1=yes
9	0=no; 1=yes	0=no; 1=yes

* www.pdaps.org

Table 2:

Item endorsement probabilities by interval

		1999–2004			2005–2009			2010–2016		
VARIABLE	**Response**	**No/Weak**	**Reactive**	**Proactive**	**No/Weak**	**Reactive**	**Proactive**	**Weak**	**Cooperative**	**Proactive**
Proactive reports to law enforcement	1=No	1.000	1.000	0.351	1.000	0.906	0.288	0.970	0.510	0.238
Proactive reports to licensing bodies	1=No	1.000	1.000	0.324	1.000	0.864	0.234	1.000	0.468	0.341
Proactive reports to prescriber/ dispenser	1=No	1.000	0.967	0.649	1.000	1.000	0.432	1.000	0.626	0.417
Access for law enforcement	1=No Access	1.000	0.100	0.189	1.000	0.000	0.266	0.333	0.000	0.182
Frequency of reporting	1=Do not report	1.000	0.083	0.000	0.952	0.053	0.000	0.265	0.000	0.000
Number of drug schedules reported	1=None	1.000	0.000	0.000	0.952	0.000	0.000	0.257	0.000	0.000
Prescriber must access	1=No	*	*	*	*	*	*	0.975	0.858	0.875
Access for prescribers	1=No Access	1.000	0.517	0.622	1.000	0.158	0.036	0.315	0.000	0.009
State shares data	1=No	*	*	*	*	*	*	0.864	0.000	0.620
Proactive reports to law enforcement	2=Yes	0.000	0.000	0.649	0.000	0.094	0.712	0.030	0.490	0.762
Proactive reports to licensing bodies	2=Yes	0.000	0.000	0.676	0.000	0.136	0.766	0.000	0.532	0.659
Proactive reports to prescriber/ dispenser	2=Yes	0.000	0.033	0.351	0.000	0.000	0.568	0.000	0.374	0.583
Access for law enforcement	2=Active/Subpoena	0.000	0.700	0.486	0.000	0.863	0.484	0.558	1.000	0.658
Frequency of reporting	2= > Weekly	0.000	0.883	0.838	0.048	0.852	0.699	0.574	0.134	0.190
Number of drug schedules reported	2= II,III,IV	0.000	0.717	0.676	0.048	0.485	0.569	0.275	0.000	0.768
Prescriber must access	2=Yes	*	*	*	*	*	*	0.025	0.142	0.125
Access for prescribers	2=Yes	0.000	0.483	0.378	0.000	0.842	0.964	0.685	1.000	0.991
State shares data	2=Yes	*	*	*	*	*	*	0.136	1.000	0.380
Access for law enforcement	3=Open Access	0.000	0.200	0.324	0.000	0.137	0.249	0.108	0.000	0.160
Frequency of reporting	3= < Weekly	0.000	0.033	0.162	0.000	0.095	0.301	0.161	0.866	0.810
Number of drug schedules reported	3=I,V(+II,III,IV)	0.000	0.283	0.324	0.000	0.515	0.431	0.469	1.000	0.232

* Variables unavailable in respective interval

Note: Provisions are organized by response option, with separate endorsement probabilities for each possible response. Provisions that have two possible response options will appear twice (for the Yes/No options), and provisions with three categories will have a separate endorsement probability for each response level.

Table 3:

Odds ratios for prior prescription opioid overdose rate predicting latent class status at time 1 for each interval (1999–2004, 2005–2009, and 2010–2016).

	Latent Status 1999		
	No/Weak	Reactive	Proactive
Overdose Rate 1998 (p<0.001)	*	0.98	1.17
	Latent Status 2005		
	No/Weak	Reactive	Proactive
Overdose Rate 2004 (p<0.001)	*	1.08	1.16
	Latent Status 2010		
	No/Weak	Reactive	Proactive
Overdose Rate 2009 (p<0.623)	*	0.94	1.02

* Indicates reference group for odds ratio comparison