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Recreational cannabis legalizations associated with reductions in prescription drug utilization among Medicaid enrollees

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Abstract

The potential substitution of cannabis for prescription medication has attracted a substantial amount of attention within the context of medical cannabis laws (MCLs). However, much less is known about the association between recreational cannabis laws (RCLs) and prescription drug use. With recent evidence supporting substitution of cannabis for prescription drugs following MCLs, it is reasonable to ask what effect RCLs may have on those outcomes. We use quarterly data for all Medicaid prescriptions from 2011 to 2019 to investigate the effect of state-level RCLs on prescription drug utilization. We estimate this effect with a series of two-way fixed effects event study models. We find significant reductions in the volume of prescriptions within the drug classes that align with the medical indications for pain, depression, anxiety, sleep, psychosis, and seizures. Our results suggest substitution away from prescription drugs and potential cost savings for state Medicaid programs.

KEYWORDS

cannabis, difference-in-differences, drug utilization, Medicaid

1 | INTRODUCTION

The landscape of cannabis policy has changed considerably in the United States since the mid 1990s. While still federally illegal, individual states have begun to adopt laws that contradict the national policy of strict cannabis prohibition. Since 1996, 38 states and the District of Columbia (DC) have passed medical cannabis laws (MCLs) which allow for legal consumption of cannabis for qualifying patients only; 18 states and the DC have passed recreational cannabis laws (RCLs) that allow for the legal consumption of personal-use cannabis for all adults over the age of 21; and finally, 17 states have passed high-CBD/low-THC laws that legalize the use of cannabidiol extract for qualifying patients (ProCon, 2022a, 2022b).

Initially, there were concerns that the liberalization of cannabis policy would act as a pathway toward broader increases in drug use. However, fears regarding the use of pharmaceuticals have largely been ameliorated, as empirical evidence has indicated that cannabis laws may in fact reduce the number of prescriptions in Medicare, Medicaid, and in the employer sponsored health insured population (Bradford & Bradford, 2016, 2017; Bradford et al., 2018; Powell et al., 2018; Shi et al., 2022; Wen & Hockenberry, 2018; Wen et al., 2021). Additionally, while preliminary evidence indicated that early adopting MCLs may have reduced opioid mortality (Bachhuber et al., 2014; Chan et al., 2019; Powell et al., 2018), more recent research indicates that the relationship between medical cannabis access and opioid mortality appears to be more tenuous than that of medical cannabis and prescription utilization (Shover et al., 2019).

If, as the overall body of evidence indicates, MCLs are in fact associated with a reduction in pharmaceutical drug use, it is reasonable to assume that RCLs would also lead to reductions in utilization. Hollingsworth et al. (2020) show increases in self-reported cannabis use by 5% following MCLs, 13% following RCLs, and 25% following RCLs with active dispensaries. Thus, since RCLs impact the entire adult population within a state as opposed to only those with active medical cannabis cards,

it seems plausible that the effect of RCLs on pharmaceutical drug utilization may be even greater than that of medical laws. This claim is bolstered by Wen and Hockenberry (2018), who found that RCLs decreased opioid specific utilization in Medicaid by a larger amount than medical laws.

In this study, we evaluate the impact of RCLs on the utilization of prescription drugs in the Medicaid population. Our analysis deviates from Wen and Hockenberry (2018) and Shi et al. (2022), who only explore the impact of RCLs on opioids, whereas we identify nine condition-specific drug classes and estimate changes in these drug classes attributable to the implementation of an RCL. In this way, we provide a more general overview of the effect of RCLs. We use a two-way fixed effects (TWFE) difference-in-differences design in an event study framework, robust to the concerns which arise with the heterogeneity in our treatment timing. Our estimates reflect reductions in six of our nine drug classes: depression, anxiety, pain, seizures, psychosis, and sleep. Our results suggest substitution away from prescription drugs and potential for discontinuities in medical care as an unintended consequence of this substitution.

2 | METHODS

This study is interested in the effect of RCLs on the utilization of prescription drugs in the Medicaid population. We use a difference-in-differences design to estimate the association between RCLs and Medicaid prescription drug utilization for nine condition-specific drug classes. Our sample captures all 50 states from 2011 to 2019 and is observed at the state-quarter-year level.

2.1 | Data

We leverage Medicaid State Drug Utilization Data (SDUD), which provides quarterly totals of drug utilization indexed at the national drug code (NDC) level, retrieved from the Centers for Medicare and Medicaid Services (CMS) data portal for years 2011–2019. These data detail drug utilization in the form of prescriptions written, units reimbursed, and dollars reimbursed by Medicaid at the state-quarter level. These data capture our primary set of outcomes - utilization at the state-quarter level for a set of nine condition-specific drug groups. We capture prescribing for both fee-for-service (FFS) and managed care (MCO) beneficiaries.

Data on our key explanatory variable of interest, RCLs, were sourced from the RAND-OPTIC center policy dataset. We attempt to adjust for changes in our study population by dividing the reimbursed units of our selected drug groups by state-level Medicaid enrollment counts retrieved from CMS. Active physician counts at the state-year level were extracted from Area Health Resource Files produced by the Health Resources and Services Administration.

2.2 | Sample

Our sample consists of 1834 state-quarter observations in all 50 states and the DC from 2011 to 2019. We begin our study window in 2011 due to changes in the Medicaid reporting standards which govern the data used in this study - the change occurred in 2010 and also reflects the first year all states were included (Wen & Hockenberry, 2018). Prior to 2011, Arizona did not report its SDUD to CMS and were not included in the SDUD data. The 11 RCL implementers in this panel are Alaska, California, Colorado, Maine, Massachusetts, Michigan, Nevada, Oregon, Vermont, and Washington.

The drugs selected for our sample follow existing literature, Bradford and Bradford (2017), and identify nine sets of prescription drugs with indications for substitutive clinical cannabis applications aligned with Orange Book condition-specific drug classes. These drugs were extracted from the SDUD data by NDC code – these NDC code lists are available on request. Appendix Table A1 reports logged means in prescription drug utilization per 100,000 Medicaid enrollees by drug class and RCL implementation status. Prescription drug use increased over our study period for both RCL and non-RCL states and while RCL states had higher levels of utilization, trends in utilization appear similar.

2.3 | Empirical strategy

We fit a series of difference-in-differences (DiD) models in an event study specification to estimate treatment effects relative to time since an RCL implementation. We face the challenge of staggered treatment timing, illustrated in Figure 1, which has the

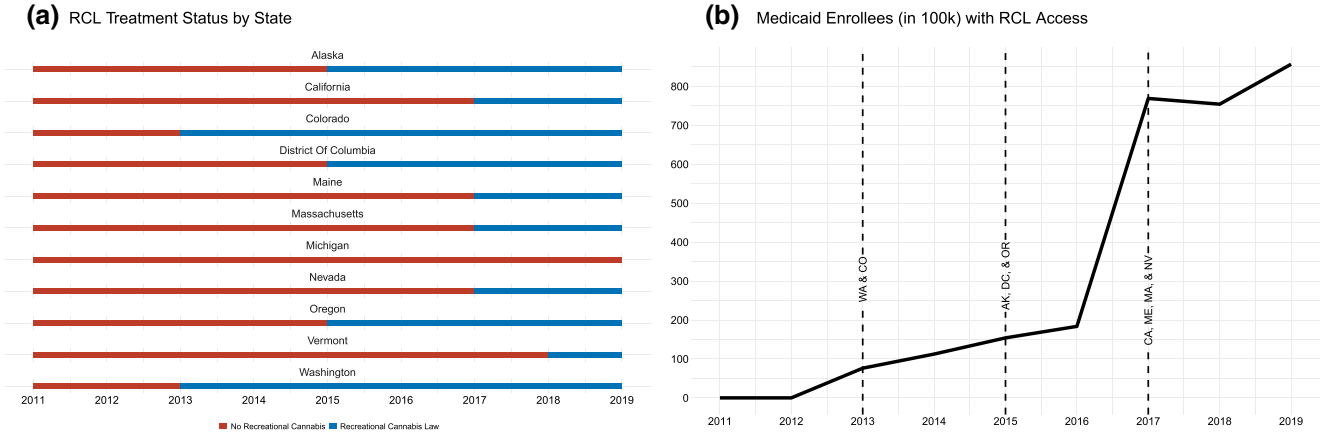

FIGURE 1 Panel A illustrates the state-level variation in recreational cannabis law (RCL) implementation among sample states for our study window (2011–2019). RCL implementation data were retrieved from the RAND Corporation's Opioid Policy Tools and Information Center. Displayed are the 11 RCL implementers in our sample and their implementation time across our study window. Michigan is shown in this panel because its RCL allowed for non-dispensary cannabis possession in the last year of our study window. Our sample includes 1834 state-quarter observations across 11 years of State Drug Utilization Data (SDUD) data. Panel B plots the total number of Medicaid enrollees, ages 21 and older, who lived in states with an active RCL within our time frame. Medicaid enrollment data were sourced from reports provided by the Centers for Medicare and Medicaid Services (CMS). [Colour figure can be viewed at wileyonlinelibrary.com]

potential to bias our difference-in-differences estimate (Goodman-Bacon, 2021). We follow the literature to assess the comparisons which compose our estimate with a Goodman-Bacon decomposition shown in Appendix Figure A2. Given the validations of our setting and composition of our DiD estimate, we opt for a canonical two-way fixed effect (TWFE) event study model which takes the following form:

$$\log(y_{st}) = \alpha + \sum_{j=-4, j\neq 1}^{3} \beta_t RCL_{st}(t = k + j) + \beta_n X_{st} + \mu_s + \tau_t + \epsilon_{st}$$

In this model, our outcome $\log(y_{st})$ is the logged prescription rate per 100,000 Medicaid enrollees for a condition-specific drug class. In the summation term $-\sum_{j=-4,j\neq 1}^{3} \beta_t RCL_{st}(t = k + j) - j$ indexes the year relative to RCL implementation for treated states – expansion occurs at $j = 0$ – and k represents the year in which a state implemented an RCL. We are interested in the coefficient β_t which represents the difference in our outcome between treated and non-treated units at time t. Our models include a vector of covariates, X_{st}, indexed at the state-year level. This specification includes covariates for unemployment rate, number of active physicians, Medicaid expansion status, and active must-access PDIMPs. See Appendix Table A1 for further details. We weight these regressions by Medicaid enrollment. We include state μ_s and time τ_t level fixed effects. Standard errors, ϵ_{st}, are clustered at the state level.

3 | RESULTS

3.1 | Baseline results

Our findings show significant reductions in the Medicaid prescribing rate relative to implementation of an RCL in six of our nine condition-specific drug classes. We find that RCLs are associated with the following condition-specific drug utilization reductions: 11.1% (95% Confidence Interval [CI] = −18.2 to −4.1) for depression, 12.2% (95% CI = −19.5 to −4.8) for anxiety, 8% (95% CI = −15.4 to −0.6) for pain, 9.5% (95% CI = −16.6 to −2.5) for seizures, 10.7% (95% CI = −17.8 to −3.6) for psychosis, and 10.8% (95% CI = −16.1 to −5.4) for sleep. We do not see a measurable change in drugs used to treat nausea, spasticity, or glaucoma following RCLs, in the Medicaid population.

We test for differential trends in treatment states prior to RCL implementation by leveraging our difference-in-differences setting in an event study specification. The lead and lag terms of our event study are illustrated visually with 95% confidence intervals in Figure 2. The lead terms included in our event study model are not jointly significant for any of these outcomes,

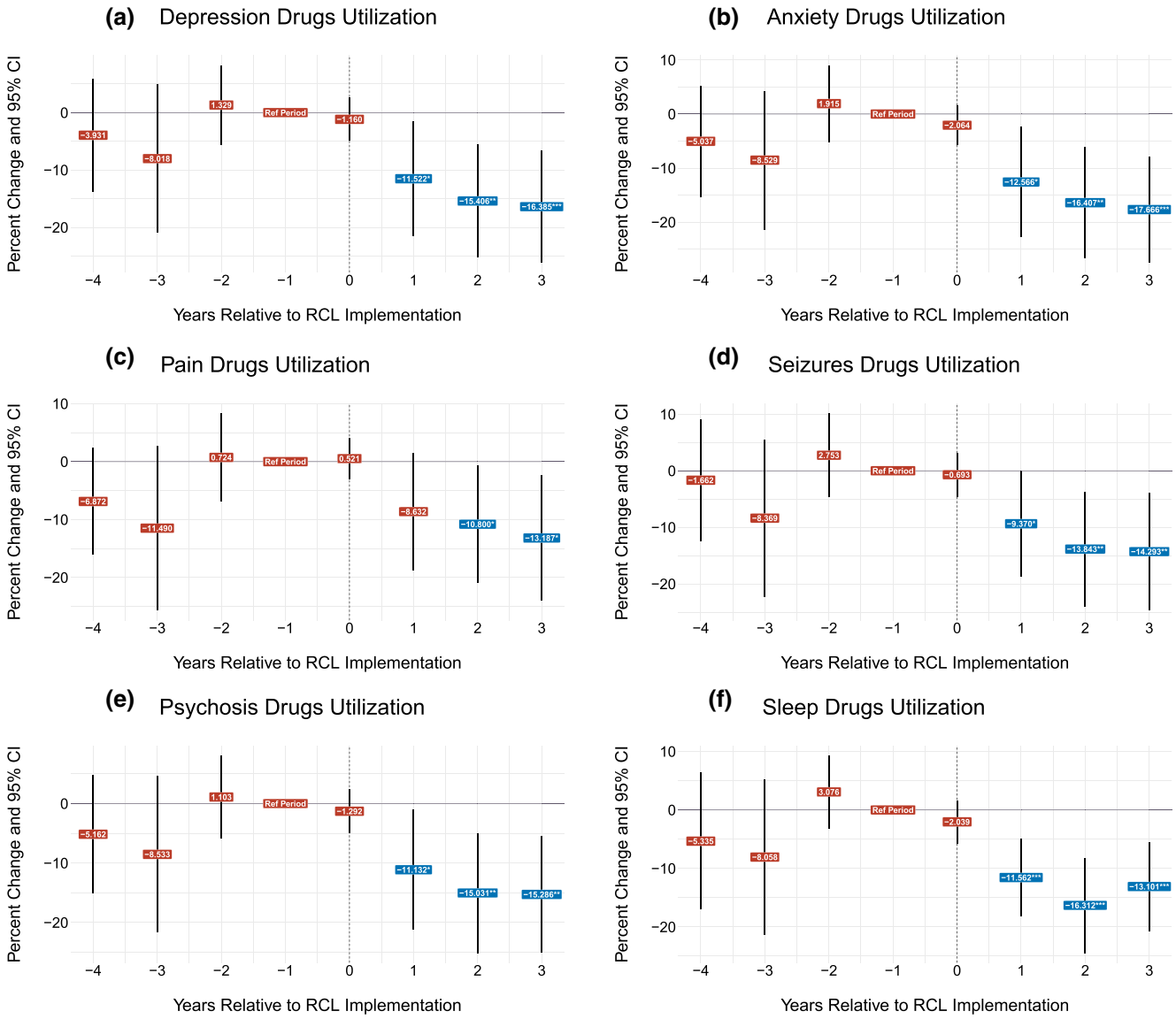

FIGURE 2 Event study estimates of recreational cannabis laws (RCLs)' impact on logged drug utilization – number of prescriptions written – per Medicaid enrollee. Estimates correspond to the baseline model described in Section 2.2. Point estimates are shown on period-specific coefficient labels and standard errors can be found in Appendix Table A2. Coefficients are transformed to represent percentage changes in rates and standard errors are expanded using the delta method to account for nonlinear transformation of the outcome variable. Drug classes are displayed as the title for each subplot. [Colour figure can be viewed at wileyonlinelibrary.com]

aiding the validation of the parallel trend assumption which underlies our method. Our full results, including period-specific coefficients, for all nine drug classes are illustrated in Appendix Figure A1 and Table A2.

3.2 | Robustness checks

We conduct two primary robustness checks which support a causal interpretation of our estimates. Our specification assumes that, absent RCL implementation, drug utilization in treated and untreated states would have trended similarly. Our event study model shows that for the 6 drug classes which see reductions in utilization following an RCL, all lead terms – the period-specific difference in utilization between treated and non-treated units – have a coefficient statistically non-different from zero. Second, to assess if these reductions are being driven by a single state's RCL implementation, we iteratively exclude states that implemented an RCL and re-estimate our primary specification. The results of this robustness check are presented in Appendix Figure A3; they reflect a negligible effect on our coefficients.

4 | DISCUSSION

This study adds to the growing body of literature surrounding the effects of RCLs on pharmaceutical utilization. While previous studies have focused on one particular type of drug (opioid), we instead construct nine condition-specific drug classes and estimate the effect of RCLs in these drug classes within the Medicaid population. Our findings reflect a reduction in Medicaid prescription drug utilization associated with RCL implementation.

There are several limitations of note. First, these data are at the state level, meaning we cannot speak to the effect of RCLs on individual-level outcomes. We also cannot investigate how these effects may differ by patient or demographic characteristics. Importantly, we also cannot speak to whether individual patients are substituting between pharmaceuticals and cannabis – we can only observe aggregate-level responses away from pharmaceuticals. This study also only identifies changes in pharmaceutical drug utilization – there may be heterogeneous effects in hospital drug utilization which would not be captured in these data. Additionally, of note is that we are unable to account for the simultaneous adoption of other state and local policy changes that may have occurred during our time period.

These results have important implications. The reductions in drug utilization that we find provide information about potential cost savings for state Medicaid programs. The results also indicate a potential harm reduction opportunity, as pharmaceutical drugs often come with dangerous side effects or – as with opioids – potential for misuse. These reductions align descriptively with Bradford and Bradford (2017) in magnitude, though we do not observe meaningful changes in drugs used to treat nausea. Rather, we estimate reductions in drugs used to treat sleep and anxiety disorders where Bradford and Bradford (2017) do not. This suggests that conditions for which prescription drugs are potentially substituted could vary between medical and RCLs.

It is important to note, however, that cannabis use is not itself without harm. The National Academies of Sciences, Engineering, and Medicine – in a report that examined over 10,000 research articles – concluded that cannabis use is associated with a potential triggering of anxiety, psychoses such as schizophrenia, and that more frequent cannabis use is moderately associated with substance use disorders (National Academies of Sciences, Engineering and Medicine, 2017). We must also consider the possibility that an increase in patients using cannabis to treat their medical conditions may have the unintended consequence of creating more distance between individuals and their medical providers. The data used in this study does not capture patient-level wellness and as such, the long run effects of substitution away from pharmaceuticals to cannabis is still unknown. Hopefully, as newer data and more robust econometric methods become available, future researchers will be able to fully decompose the costs and benefits associated with the legalization of cannabis at the state level.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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APPENDIX

TABLE A1

	RCL Implementors		Non-RCL States
	Pre-RCL	Post-RCL	Full Sample
Depression Drugs			
Prescriptions per 100k Enrollees	40315.34	40342.68	43592.26
Logged Rate per 100k Enrollees	10.60	10.61	10.68
Anxiety Drugs			
Prescriptions per 100k Enrollees	37150.12	37678.04	39058.11
Logged Rate per 100k Enrollees	10.52	10.54	10.57
Nausea Drugs			
Prescriptions per 100k Enrollees	12562.36	13869.16	16934.61
Logged Rate per 100k Enrollees	9.44	9.54	9.74
Pain Drugs			
Prescriptions per 100k Enrollees	88523.14	90445.23	98763.01
Logged Rate per 100k Enrollees	11.39	11.41	11.50
Seizures Drugs			
Prescriptions per 100k Enrollees	36867.80	34326.98	37374.23
Logged Rate per 100k Enrollees	10.52	10.44	10.53

TABLE A1 (Continued)

	RCL Implementors		Non-RCL States
	Pre-RCL	Post-RCL	Full Sample
Psychosis Drugs			
Prescriptions per 100k Enrollees	44702.44	43446.10	48892.48
Logged Rate per 100k Enrollees	10.71	10.68	10.80
Sleep Drugs			
Prescriptions per 100k Enrollees	28903.42	25982.33	31602.09
Logged Rate per 100k Enrollees	10.27	10.17	10.36
Spasticity Drugs			
Prescriptions per 100k Enrollees	3307.17	3747.85	3557.77
Logged Rate per 100k Enrollees	8.10	8.23	8.18
Regression Covariates			
Proportion with Medical Cannabis Law	0.96	1.00	0.34
Proportion Expanded Medicaid	0.48	0.86	0.36
Unemployment Rate	0.07	0.05	0.05
Active MDs	34482.90	30346.12	25951.09
Medicaid Enrollment (in 100k)	17.52	17.10	11.83

Note: This table displays summary statistics for our main study sample from 2011 to 2019. For each drug class listed, we first show the number of prescriptions per 100,000 Medicaid enrollees, followed by the logged rate of prescribing. For RCL implementation states, summary statistics are split by treatment timing (before and after implementation). For non-RCL states, full sample means are displayed. All drug utilization data are sourced from Medicaid State Drug Utilization Data (SDUD), covariate data sources are detailed in Section 2.

TABLE A2

Event Time	Depression Drugs	Anxiety Drugs	Nausea Drugs	Pain Drugs	Seizure Drugs	Psychosis Drugs	Sleep Drugs	Spasticity Drugs	Glaucoma Drugs
−4	−3.931	−5.037	−11.259**	−6.872	−1.662	−5.162	−5.335	−4.924	−11.533**
	(5.010)	(5.217)	(3.434)	(4.698)	(5.489)	(5.078)	(5.976)	(4.558)	(3.749)
−3	−8.018	−8.529	−13.257*	−11.490	−8.369	−8.533	−8.058	−7.160	−14.788*
	(6.571)	(6.547)	(6.706)	(7.232)	(7.085)	(6.679)	(6.776)	(6.043)	(6.854)
−2	1.329	1.915	2.484	0.724	2.753	1.103	3.076	2.493	(5.206)
	(3.524)	(3.612)	(3.970)	(3.894)	(3.790)	(3.548)	(3.165)	(5.206)	(4.048)
0	−1.160	−2.064	0.686	0.521	−0.693	−1.292	−2.039	0.808	5.184**
	(1.921)	(1.848)	(2.165)	(1.817)	(1.993)	(1.884)	(1.865)	(2.518)	(1.807)
1	−11.522*	−12.566*	−5.238	−8.632	−9.370*	−11.132*	−11.562***	−6.318	−0.376
	(5.098)	(5.206)	(5.333)	(5.146)	(4.771)	(5.133)	(3.369)	(4.600)	(4.496)
2	−15.406**	−16.407**	−7.006	−10.800*	−13.843**	−15.031**	−16.312***	−9.815	−0.905
	(5.025)	(5.234)	(5.253)	(5.146)	(5.173)	(5.133)	(4.138)	(5.669)	(4.412)
3	−16.385***	−17.666***	−10.320	−13.187*	−14.293**	−15.286**	−13.101***	−4.802	−0.701
	(4.968)	(4.995)	(5.660)	(5.518)	(5.297)	(4.974)	(3.889)	(5.301)	(6.005)
RCL DiD	−11.118**	−12.176**	−5.470	−8.024*	−9.550**	−10.685**	−10.753***	−5.032	0.801
	(3.600)	(3.743)	(4.024)	(3.770)	(3.580)	(3.635)	(2.710)	(3.807)	(3.671)
Leads	−3.540	−3.884	−7.344	−5.879	−2.426	−4.197	−3.439	−3.197	−8.278*
	(4.345)	(4.344)	(3.764)	(4.472)	(4.374)	(4.471)	(4.644)	(4.303)	(4.003)

Note: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Event study coefficients at each period provided with state-clustered robust standard errors in parentheses. This specification includes covariates for unemployment, number of active physicians, Medicaid expansion status, and active PDMPs. We use state and year fixed effects. Our outcome variables – condition-specific drug utilization – are logged and as such we have transformed the estimates above by $100 * (\exp(\beta) - 1)$) and the standard errors have been adjusted accordingly using a delta method expansion and nlcom method. Estimates can be interpreted as a percentage change in period-specific number of prescriptions written of a given set of outcome drugs in the Medicaid population. The coefficient "RCL DiD" is the average of the linear combination of lagged terms in each specification – our difference-in-differences estimate. The event study reference period (-1) is omitted from this table.

FIGURE A1 [Colour figure can be viewed at wileyonlinelibrary.com]

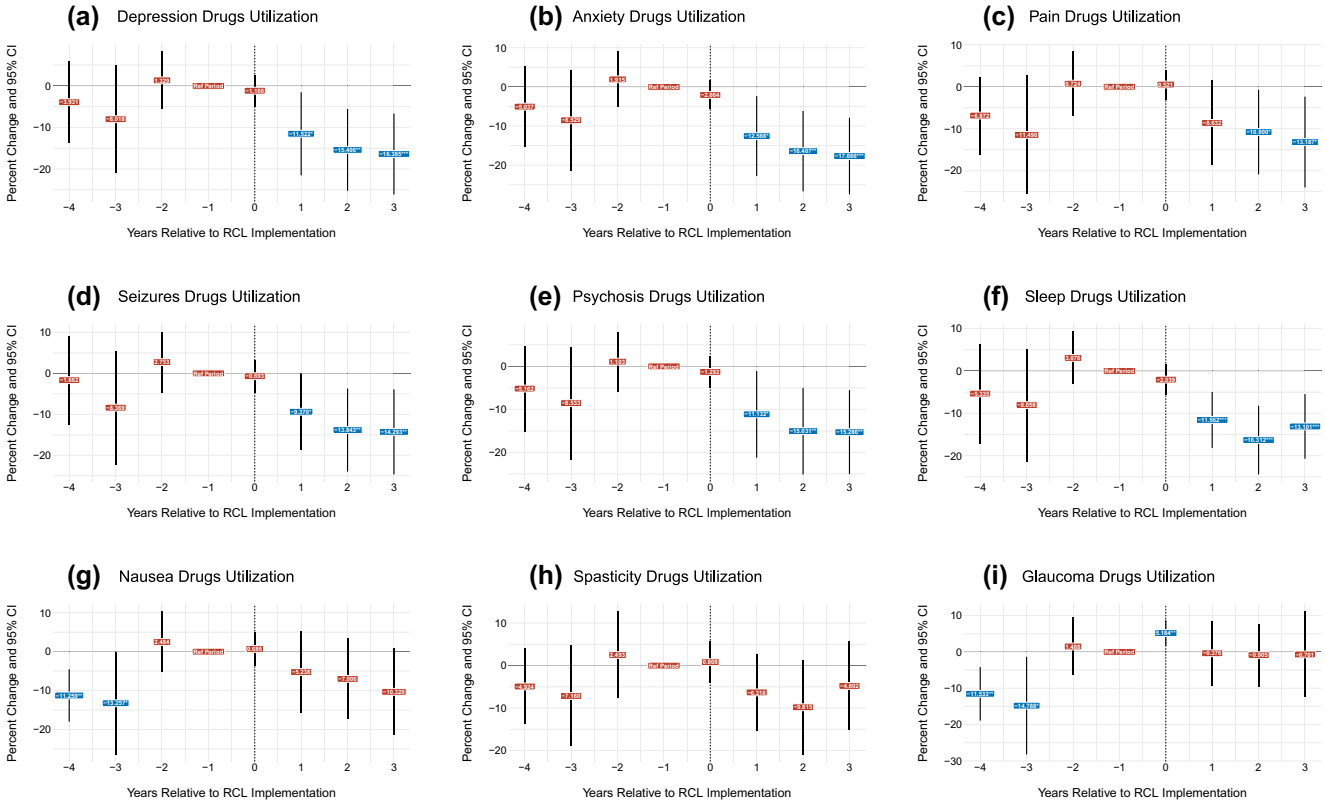

FIGURE A2

We perform a Goodman-Bacon decomposition and show that 91.2% of the unadjusted difference-in-difference estimate is composed of valid comparisons between treated and untreated units.

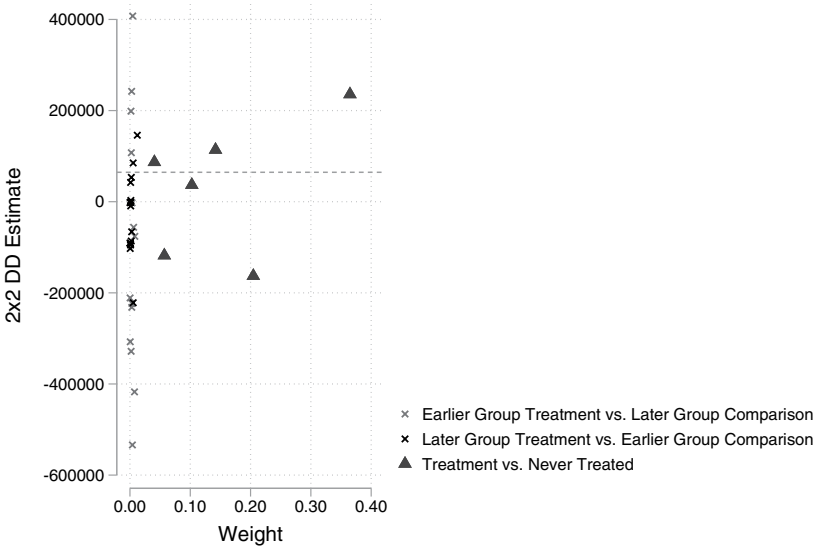

FIGURE A3

We perform an exclusion analysis where we iteratively drop states which implemented an RCL to evaluate if our estimate is being driven by effects in a single treated state. The figure below shows the distribution of coefficients and standard errors across these iterative analyses for each drug class we study.