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# Association Between State Policies on Improving Opioid Prescribing in 2 States and Opioid Overdose Rates Among Reproductive-aged Women

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## Abstract

**Background:** The opioid overdose epidemic has been declared a public health emergency. Women are more likely than men to be prescribed opioid medications. Some states have adopted policies to improve opioid prescribing, including prescription drug monitoring programs (PDMPs) and pain clinic laws.

**Objective:** Among reproductive-aged women, we examined the association of mandatory use laws for PDMPs in Kentucky (concurrent with a pain clinic law) and New York with overdose involving prescription opioids or heroin and opioid use disorder (OUD).

**Study Design, Subjects, and Outcome Measures:** We conducted interrupted time series analyses estimating outcome changes after policy implementation in Kentucky and New York, compared with geographically close states without these policies (comparison states), using 2010–2014 State Inpatient and State Emergency Department Databases. Outcomes included rates of inpatient discharges and emergency department visits for overdoses involving prescription opioids or heroin and OUD among reproductive-aged women.

**Results:** Relative to comparison states, following Kentucky's policy change, we found an immediate postpolicy decrease and a decreasing trend in the rate of overdoses involving

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The findings and conclusions in this article are those of the authors and do not necessarily represent the official position of the Centers for Disease Control and Prevention.

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prescription opioids, an immediate postpolicy increase in the rate of overdoses involving heroin, and a decreasing trend in the OUD rate (*P*<0.01); New York's policy change was not associated with the assessed outcomes.

**Conclusions:** PDMPs and pain clinic laws, such as those implemented in Kentucky, may be promising strategies to reduce the adverse impacts of high-risk opioid prescribing among reproductive-aged women. As states continue efforts to improve inappropriate opioid prescribing, similar strategies as those adopted in Kentucky merit consideration.

**Keywords**

prescription opioid; heroin; prescription drug monitoring program; pain clinic laws; women of reproductive age

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In the United States, the opioid overdose epidemic has been declared a public health emergency.[1] Rising opioid overdose rates have been linked to increases in high-risk opioid prescribing.[2] Opioid use among reproductive-aged and pregnant women is of particular concern. In 2018, the odds of filling an opioid prescription for reproductive-aged women was 1.5–2.0 times that of men.[3] The rate of opioid use disorder (OUD) at delivery quadrupled from 1999 to 2014.[4,5] OUD during pregnancy is associated with adverse outcomes including maternal mortality, preterm labor, and neonatal abstinence syndrome (NAS).[6-10] From 2004 to 2016, the rate of NAS in the United States increased by >5-fold.[11] In 2016, the total cost of in-hospital births with a NAS diagnosis was $572.7 million.[12] Upstream interventions to reduce unnecessary opioid use among reproductive-aged women may be a promising strategy.[12]

To reduce the risk of opioid-involved adverse events, many states have implemented policies to improve controlled substance prescribing. One such policy is the statewide prescription drug monitoring program (PDMP), which was implemented by all states and DC, as of 2018, except for Missouri.[13] PDMPs are statewide, electronic databases that collect pharmacy data on filled controlled substance prescriptions with the potential for misuse, including opioids.[13] Prescribers and dispensers can use PDMPs to monitor patients' prescriptions of controlled substances and identify risk factors for overdose, which has the potential to combat the opioid crisis.[14-18] Comprehensive PDMP mandatory use laws ("comprehensive use mandates" thereafter), which were adopted in several states, commonly refer to those that cover all practitioners (regardless of specialty) and require checking the PDMP before prescribing an opioid.[14,18] This study evaluates whether the comprehensive use mandates implemented by Kentucky (KY) and New York (NY) in July 2012 and August 2013, respectively, reduced rates of opioid-related overdoses and OUD among reproductive-aged women.

There are differences in comprehensive use mandates in KY versus NY that might lead to different effects (Appendix S1, Supplemental Digital Content 1, http://links.lww.com/MLR/C156).[14] While both KY and NY required providers to query the PDMP every time before prescribing opioids or during opioid treatment, KY required query when receiving information on patient's misuse of opioids. KY also mandated providers to register for the PDMP database before prescribing opioids[14]; 95% of practitioners authorized to prescribe controlled substances were registered with PDMPs in KY as of July 2013.[19] KY also expanded staff to support PDMP operations, developed user-friendly interfaces, and updated data frequently, which further increased the utility of the PDMP.[20] Furthermore, KY implemented a pain clinic law concurrent with PDMP mandates. Thus, we hypothesized that the mandates in KY would have a larger effect on opioid-related outcomes than in NY.

## METHODS

### Data

We used the 2010–2014 State Inpatient Databases (SID) and State Emergency Department Databases (SEDD) from the Healthcare Cost and Utilization Project (HCUP) of the Agency for Healthcare Research and Quality.[21,22] These databases contain data on hospital inpatient discharges and emergency department (ED) visits of nonfederal community hospitals in participating states.[21,22]

The selection of the states for inclusion was based on the effective date of the comprehensive use mandate[14] and the availability of data. KY and NY were included as “treatment” states as they enacted comprehensive use mandates during our study period and contributed data for at least 1 year before and after mandate implementation.[14,18,23]

For each treatment state, we identified a comparison state that was geographically close and without a comprehensive use mandate during the study period. North Carolina (NC) and New Jersey (NJ) were selected as comparison states for KY and NY, respectively. NC later passed a PDMP mandate in June 2017, and NJ passed a PDMP mandate at the end of 2015.[24-26]

### Outcome Measures

We assessed monthly rates of inpatient discharges and ED visits associated with an OUD or an overdose diagnosis involving: (1) prescription opioids; (2) heroin; and (3) prescription opioids or heroin. OUD and overdoses were identified using the International Classification of Diseases, Ninth Revision, Clinical Modification (*ICD-9-CM*), diagnosis codes.[27,28] OUD included codes for opioid abuse or dependence,[29] and overdose included codes for incidences of prescription opioid or heroin poisoning; it is possible for an individual to have had codes for both (Appendix S2, Supplemental Digital Content 1, http://links.lww.com/MLR/C156). For each outcome, the numerator included all inpatient discharges and ED visits with applicable diagnosis codes among reproductive-aged women (sample size detailed in Appendix S3, Supplemental Digital Content 1, http://links.lww.com/MLR/C156), and the denominator included the total number of reproductive-aged women in the state by year from US Census population data.[30] Rates were expressed per 100,000 reproductive-aged women.

### Statistical Analysis

We conducted a comparative interrupted time series (ITS) analysis comparing outcome changes after law implementation in treatment states to respective comparison states, by calculating the difference in the monthly outcome between the treatment state and its comparison state.[14,31] As indicated in prior research, this approach relaxes the assumption of prepolicy trends.[32] Segmented linear regression models were used to assess changes in outcome *level* (estimated difference in the outcome in the month immediately before versus immediately after policy implementation) and *slope* (estimated change in the outcome's time trend after the policy change) associated with the policy change.[31,33] We also estimated the absolute and relative policy effects at the 12th month following implementation.[14,34] In all models, we accounted for autocorrelation.[31]

Changes in population composition over time might confound the policy effects.[33,35] We explored the trends of population characteristics, including age, sex, race/ethnicity, education, and state unemployment and poverty rates during 2010–2014. Because none of these characteristics changed substantially over time during our study period, they were not controlled for in our models.[35]

Analyses were conducted using SAS (Version 9.4)[36] and Stata (Version 14.0)[37] statistical software.

# RESULTS

## Prescription Opioid-involved Overdose

In KY, the average rate of prescription opioid-involved overdose was 6.44 per 100,000 reproductive-aged women per month prepolicy (Table 1) and decreased by 2.95 per 100,000 (46% relative reduction) in the first month postpolicy, compared with NC ($P < 0.01$) (Fig. 1, Table 1). Postpolicy, the prescription opioid-involved overdose trend (slope changes = −0.10/100,000; $P < 0.01$) declined compared with NC. By the 12th month postpolicy, KY had an absolute reduction of 4.19 per 100,000 (87% relative reduction) in prescription opioid-involved overdoses, compared with NC.

In NY, the rate of prescription opioid-involved overdose was an average of 2.21 per 100,000 per month prepolicy. Postpolicy, there was neither an immediate level change ($P = 0.365$) nor a significant trend ($P = 0.401$) in prescription opioid-involved overdose in NY, relative to NJ (Fig. 1, Table 1).

## Heroin-involved Overdose

In KY, the average prepolicy rate of heroin-involved overdose was 1.27 per 100,000 per month (Table 1) and increased by 1.30 per 100,000 [102% relative increase (1.30/1.27)] in the first month postpolicy (Fig. 2, Table 1). Postpolicy, the trend of heroin-involved overdose did not change, relative to NC ($P = 0.942$).

NY's prepolicy heroin-involved overdose rate was, on average, 0.74 per 100,000 per month. Postpolicy, there was neither an immediate level change ($P = 0.578$) nor a significant trend ($P = 0.066$) in heroin-involved overdose in NY, relative to NJ.

### Overdose Involving Prescription Opioid or Heroin

When examining overdoses involving prescription or heroin opioid, there was no postpolicy change in either KY or NY, relative to their respective comparison states ($P > 0.05$; Fig. 3, Table 1).

### Opioid Use Disorder

Postpolicy in KY, there was no immediate change in OUD rate ($P = 0.756$) (Fig. 4, Table 1), but there was a declining trend in OUD (slope change = −0.58/100,000; $P = 0.002$), relative to NC. By the 12th month postpolicy, KY had an absolute reduction of 6.64 per 100,000 (14% relative reduction) in the OUD rate, compared with NC. There was not an immediate change or trend in the OUD rate postpolicy in NY compared with NJ ($P > 0.1$).

## DISCUSSION

Our study provides the first estimates of changes in rates of overdoses involving prescription opioids and heroin and OUD among reproductive-aged women associated with the implementation of comprehensive use mandates intended to reduce high-risk opioid prescribing. We found that, in KY, there was an immediate and sustained reduction in the rate of prescription opioid-involved overdose and a potential shift toward heroin-involved overdose among reproductive-aged women after the comprehensive use mandates. There was no evidence that NY's mandates had an effect on the outcomes. These findings were consistent with recent analyses in the general population that found reductions in the opioid dosage prescribed, number of opioid fills, and prescription opioid deaths in some states implementing PDMP mandates, including KY.[14,15,18] Prior studies also reported limited effects of PDMP mandates in NY on curbing the opioid epidemic.[14,27]

The significant postpolicy outcome changes in KY, as opposed to NY, are consistent with our hypothesis. Comprehensive use mandates in KY were more extensive than in NY, as described earlier. The staffing support for using PDMPs, mandatory provider registering, and concurrent pain clinic law in KY may have contributed to the observed effect. Furthermore, KY had a higher baseline rate of opioid prescribing than NY. KY also had an upward trend in prescription opioid-involved overdose prepolicy, whereas the prepolicy trend in NY was almost flat (Fig. 1). All these factors may have allowed a greater opportunity for PDMPs to have an impact in KY than in NY.

We found a significant increase in heroin-involved overdoses immediately following KY's mandates. This finding suggests a possible shift from prescription opioid-involved overdose to heroin-related overdose,[27,38] which may explain the nonsignificant change observed for overdoses overall. There may be other explanations for the increase in heroin-involved overdoses, particularly the low cost and high purity of heroin available in recent years.[39] Given the concern that PDMP mandates and pain clinic laws might unintentionally increase illicit drug use, tactics aimed at addressing potential increases in heroin use and better access to OUD treatment are worth considering when implementing state policies to improve opioid prescribing.

Our analysis has limitations. Measurement errors might exist. Particularly, the HCUP data could not capture OUD diagnosed outside of inpatient and emergency settings. Using *ICD-9-CM* codes, we were unable to differentiate OUD diagnoses attributed to prescription opioids from those due to heroin, with the former being the target of PDMPs. Similarly, the *ICD-9-CM* codes used to identify heroin and prescription opioid-involved overdoses may include other opioids like illicitly manufactured fentanyl.[40] Future studies may use *ICD-10-CM* codes from more recent years to better disentangle substance type.[41]

Our findings generated from 2 states may not be generalizable to other states. We cannot disentangle the effect of KY's comprehensive use mandates from that of concurrent pain clinic laws. Similarly, there might be estimation bias due to the concurrent implementation of other programs addressing opioid misuse in the states. Nonetheless, to our knowledge, there was no other major public health efforts at the state level during our study period. In addition, there might be concern about cross-contamination: residents in NY may cross the border to NJ to obtain prescription opioids. However, the single ITS in NJ showed no change in overdose involving prescription opioids after NY's mandates (results available upon request).

For several outcomes, the treatment and comparison states had slightly different prepolicy trends. As the ITS method does not require prepolicy parallel trends assumption, and state characteristics remained stable during the study period, the potential influence of this limitation was minimal. The segmented regression model assumed a linear functional form. However, a linear model may obscure some large monthly variations [eg, postpolicy changes in heroin overdose rates in KY (Fig. 2)]. In addition, the per-month-per-state number of ED and inpatient discharges associated with heroin overdose was small (Appendix S3, Supplemental Digital Content 1, http://links.lww.com/MLR/C156), which may reduce the power to detect a difference. Last, SID excludes hospitals in institutional settings, such as mental health or substance use treatment centers, where rates of opioid overdose and OUD may be higher.

Despite these limitations, our findings suggest that mandatory PDMP use combined with mandatory registration and pain clinic laws, as implemented in KY, could be a promising strategy to reduce prescription opioid-involved overdoses and mitigate increases in OUD among reproductive-aged women. Along with state opioid prescribing policies, additional multiprong public health interventions are needed to reduce heroin overdoses, address the treatment needs of reproductive-aged women, and ensure the optimal downstream health outcomes of mothers and infants.[39,42]

## Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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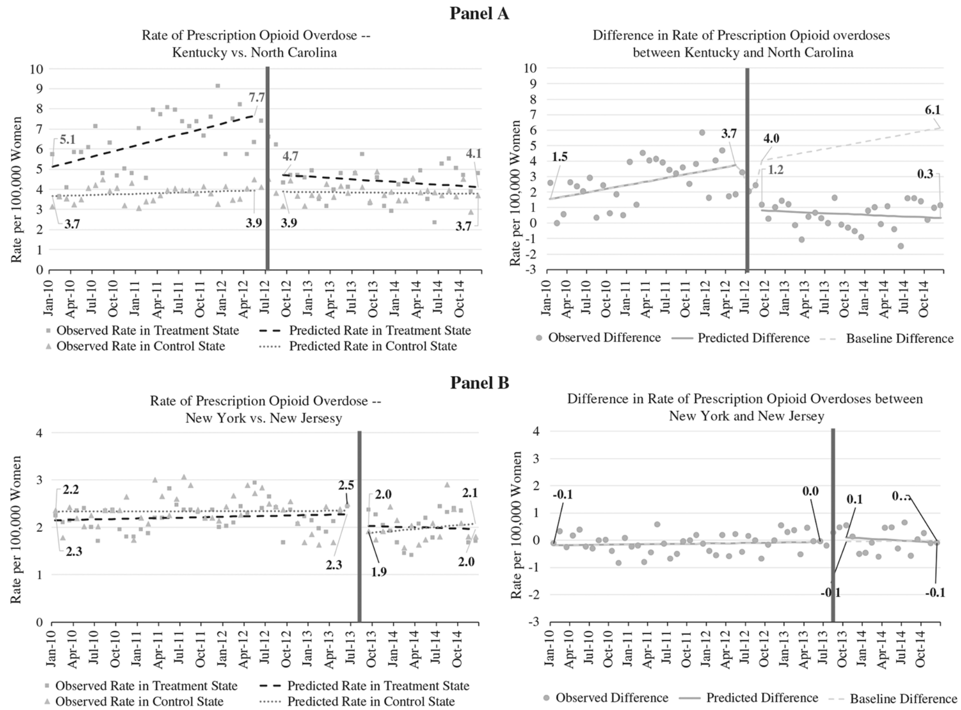


**FIGURE 1.**

Monthly rate of emergency department and inpatient discharges for overdoses involving prescription opioids, per 100,000 reproductive-aged women in the state, 2010–2014. Panel A, Kentucky versus North Carolina. Panel B, New York versus New Jersey. A fitted regression (solid) line in the figures on the right panel shows the difference between the predicted monthly outcomes for the treatment state and the corresponding comparison state before and after the month when the policy was implemented; the dashed line was the predicted difference of the monthly outcomes between the treatment and comparison states after the policy implementation month if the policy was not implemented (the counterfactual). The dots are the difference of the observed outcomes between the treatment state and the corresponding comparison state in each month. The dotted lines in the figures on the left panel show the predicted outcomes from the interrupted time series regression for each data point in each individual state. The square and triangle dots are the observed outcomes in the treatment state and the comparison state, respectively, in each month. Apr indicates April; Jan, January; Jul, July; Oct, October. *Source*: Authors' analyses of 2010–2014 HCUP State Inpatient Databases and State Emergency Department Databases.

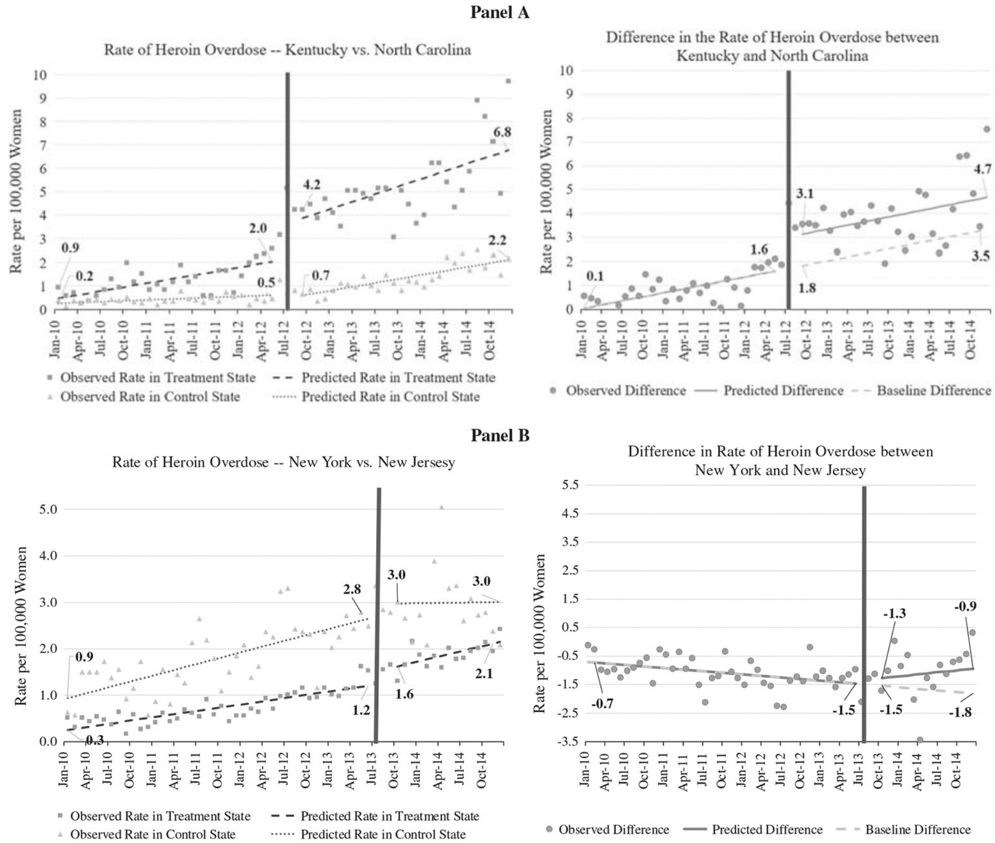


**FIGURE 2.**

Monthly rate of emergency department and inpatient discharges for overdoses involving heroin, per 100,000 reproductive-aged women in the state, 2010–2014. Panel A, Kentucky versus North Carolina. Panel B, New York versus New Jersey. A fitted regression (solid) line in the figures on the right panel shows the difference between the predicted monthly outcomes for the treatment state and the corresponding comparison state before and after the month when the policy was implemented; the dashed line was the predicted difference of the monthly outcomes between the treatment and comparison states after the policy implementation month if the policy was not implemented (the counterfactual). The dots are the difference of the observed outcomes between the treatment state and the corresponding comparison state in each month. The dotted lines in the figures on the left panel show the predicted outcomes from the interrupted time series regression for each data point in each individual state. The square and triangle dots are the observed outcomes in the treatment state and the comparison state, respectively, in each month. Apr indicates April; Jan, January; Jul, July; Oct, October. *Source*: Authors' analyses of 2010–2014 HCUP State Inpatient Databases and State Emergency Department Databases.

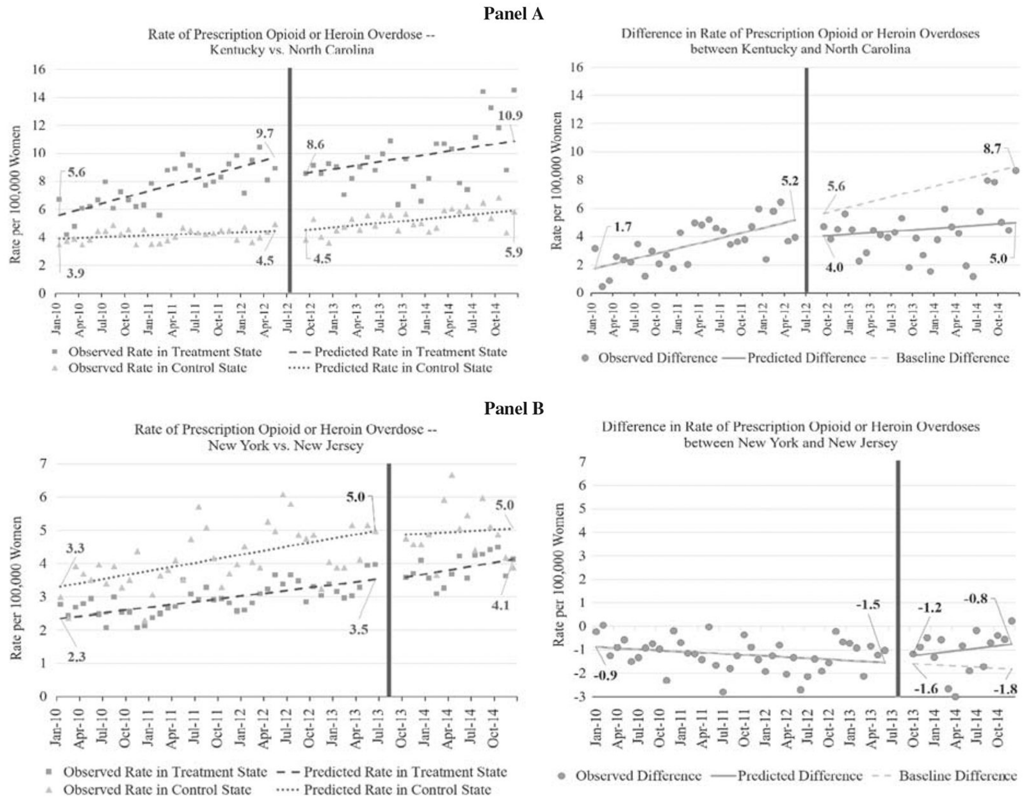


**FIGURE 3.**

Monthly rate of emergency department and inpatient discharges for overdoses involving prescription opioid or heroin combined, per 100,000 reproductive-aged women in the state, 2010–2014. Panel A, Kentucky versus North Carolina. Panel B, New York versus New Jersey. A fitted regression (solid) line in the figures on the right panel shows the difference between the predicted monthly outcomes for the treatment state and the corresponding comparison state before and after the month when the policy was implemented; the dashed line was the predicted difference of the monthly outcomes between the treatment and comparison states after the policy implementation month if the policy were not be implemented (the counterfactual). The dots are the difference of the observed outcomes between the treatment state and the corresponding comparison state in each month. The dotted lines in the figures on the left panel show the predicted outcomes from the interrupted time series regression for each data point in each individual state. The square and triangle dots are the observed outcomes in the treatment state and the comparison state, respectively, in each month. Apr indicates April; Jan, January; Jul, July; Oct, October. *Source*: Authors' analyses of 2010–2014 HCUP State Inpatient Databases and State Emergency Department Databases.

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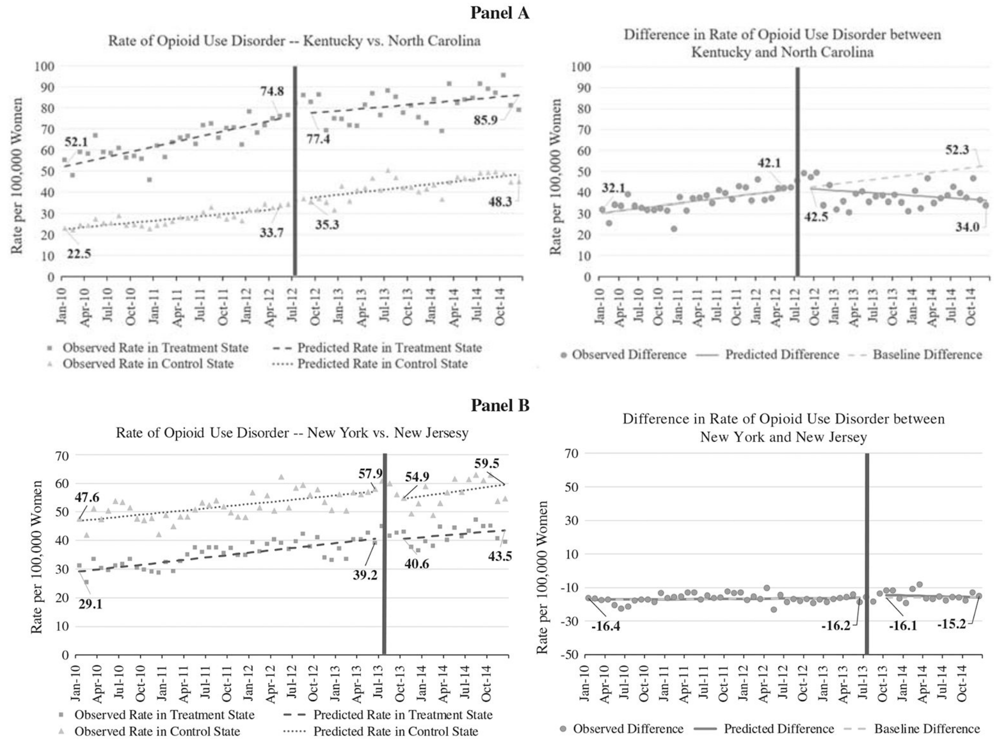


**FIGURE 4.**

Monthly rate of opioid use disorder-related emergency department and inpatient discharges, per 100,000 reproductive-aged women in the state, 2010–2014. Panel A, Kentucky versus North Carolina. Panel B, New York versus New Jersey. A fitted regression (solid) line in the figures on the right panel shows the difference between the predicted monthly outcomes for the treatment state and the corresponding comparison state before and after the month when the policy was implemented; the dashed line was the predicted difference of the monthly outcomes between the treatment and comparison states after the policy implementation month if the policy was not implemented (the counterfactual). The dots are the difference of the observed outcomes between the treatment state and the corresponding comparison state in each month. The dotted lines in the figures on the left panel show the predicted outcomes from the interrupted time series regression for each data point in each individual state. The square and triangle dots are the observed outcomes in the treatment state and the comparison state, respectively, in each month. Apr indicates April; Jan, January; Jul, July; Oct, October. *Source*: Authors' analyses of 2010–2014 HCUP State Inpatient Databases and State Emergency Department Databases.

## TABLE 1.

Changes in the Outcomes Associated With the Opioid Prescribing Policies in Reproductive-aged Women in Kentucky and New York, Relative to the Comparison States

| | Rate of Prescription Opioid–involved Overdose (Per 100,000 Reproductive-aged Women)* | | | Rate of Heroin-involved Overdose (Per 100,000 Reproductive-aged Women)* | | | Rate of Prescription Opioid–involved or Heroin-involved Overdose (Per 100,000 Reproductive-aged Women)* | | | Rate of OUD (Per 100,000 Reproductive-aged Women)* | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Changes in Outcomes** | **Estimate** | **SE** | ***P*** | **Estimate** | **SE** | ***P*** | **Estimate** | **SE** | ***P*** | **Estimate** | **SE** | ***P*** |
| Average monthly rate before the policy change in Kentucky | 6.44 | | | 1.27 | | | 7.71 | | | 63.74 | | |
| Difference between Kentucky and North Carolina | | | | | | | | | | | | |
| Level change immediately following policy implementation | **−2.95** | **0.60** | **<0.001** | **1.30** | **0.45** | **0.005** | −1.34 | 0.79 | 0.097 | 0.89 | 2.85 | 0.756 |
| Trend change | **−0.10** | **0.03** | **0.007** | 0.002 | 0.02 | 0.942 | −0.09 | 0.05 | 0.062 | **−0.58** | **0.18** | **0.002** |
| Outcome change at the 12th month following policy implementation† | | | | | | | | | | | | |
| Absolute change (95% CI) | −4.19 (−5.63, −2.75) | | | 1.32 (0.29, 2.35) | | | −3.95 (−7.02, −0.88) | | | −6.64 (−13.78, 0.50) | | |
| Relative change (95% CI) | −87% (−97%, −78%) | | | 55% (−10%, 120%) | | | −44% (−66%, −23%) | | | −14% (−28%, −1%) | | |
| Average monthly rate before the policy change in New York | 2.21 | | | 0.74 | | | 2.95 | | | 35.44 | | |
| Difference between New York and New Jersey | | | | | | | | | | | | |
| Level change immediately following policy implementation | 0.21 | 0.23 | 0.365 | 0.14 | 0.26 | 0.578 | 0.19 | 0.43 | 0.659 | 1.95 | 1.63 | 0.236 |
| Trend change | −0.02 | 0.02 | 0.401 | 0.04 | 0.02 | 0.066 | 0.05 | 0.04 | 0.178 | −0.12 | 0.14 | 0.402 |
| Outcome change at the 12th month following policy implementation† | | | | | | | | | | | | |
| Absolute change (95% CI) | −0.01 (−0.42, 0.40) | | | 0.69 (0.32, 1.07) | | | 1.06 (0.09, 2.02) | | | 0.40 (−2.54, 3.34) | | |
| Relative change (95% CI) | —‡ | | | −40% (−58%, −23%) | | | −58% (−98%, −18%) | | | −3% (−21%, 16%) | | |

Bold values indicate statistically significant ($P < 0.05$).

Segmented time series regression models were conducted to measure the change of outcomes associated with policy implementation. Level change is measured as the predicted difference in the outcome between treatment and comparison states in the month immediately before and immediately after the policy implementation month; trend change is measured as the change of slope in the outcomes after the policy was implemented.

* The outcome measures were not mutually exclusive; <4% of encounters with an OUD diagnosis also had a diagnosis of an overdose involving opioids, and approximately one third of encounters with an overdose involving opioids also had an OUD diagnosis. In addition, about 1% of overdose records involved both prescription opioids and heroin.

† We used regression results to estimate the absolute and relative policy effect 12 months after the policies were implemented in the states, using the multivariate delta method. Absolute change in the outcome was defined as the difference between predicted outcomes with and without the policy change at the 12th month following the policy change. Relative change in the outcome was defined as the ratio of the absolute change to the predicted outcome without the policy change at the 12th month following the policy change.

‡This relative change's confidence interval was nearly infinite because the value of counterfactual (outcome estimate without policy change—ie, the denominator of calculating the variance of the relative change) was nearly zero. CI indicates confidence interval; OUD, opioid use disorder.

*Source*: Authors' analyses of 2010–2014 Healthcare Cost and Utilization Project State Inpatient Databases and State Emergency Department Databases.