

# Assessing The Impact of A Restrictive Opioid Prescribing Law in West Virginia

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## Research

**Keywords:** opioids, law, prescription opioids, opiates, interrupted time series

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47 **Abstract**

48 **Background:** The Opioid Reduction Act (SB 273) took effect in West Virginia in June 2018.  
49 This legislation limited ongoing chronic opioid prescriptions to 30 days' supply, and first-time  
50 opioid prescriptions to 7 days' supply for surgeons and 3 days' for emergency rooms and dentists.  
51 The purpose of this study was to determine the effect of this legislation on reducing opioid  
52 prescriptions in West Virginia, with the goal of informing future similar policy efforts.

53 **Methods:** Data were requested from the state Prescription Drug Monitoring Program (PDMP)  
54 including overall number of opioid prescriptions, number of first-time opioid prescriptions,  
55 average daily morphine milligram equivalents (MME) and prescription duration (expressed as  
56 "day's supply") given to adults during the 64 week time periods before and after legislation  
57 enactment. Statistical analysis was done utilizing an autoregressive integrated moving average  
58 (ARIMA) interrupted time series analysis to assess impact of both legislation announcement and  
59 enactment while controlling secular trends and considering autocorrelation trends.  
60 Benzodiazepine prescriptions were utilized as a control.

61 **Results:** Our analysis demonstrates a statistically significant decrease in overall state opioid  
62 prescribing as well as average daily MME associated with the date of the legislation's enactment  
63 when considering serial correlation in the time series and accounting for pre-intervention trends.  
64 There was no such association found with benzodiazepine prescriptions.

65 **Conclusion:** Results of the current study suggest that SB 273 was associated with an average  
66 22.1% decrease of overall opioid prescriptions and a small overall decrease of average daily MME  
67 relative to the date of legislative implementation in West Virginia. There was, however, no  
68 association of the legislation on first-time opioid prescriptions or days' supply of opioid

69 medication, and all variables were trending downward prior to implementation of SB 273. The  
70 control demonstrated no relationship to the law.

71 Keywords: opioids, law, prescription opioids, opiates, interrupted time series

72

## 73 **1. Introduction**

74 Prescription drug misuse is the administration of a prescription drug in a way not intended  
75 by the prescriber [1]. This can include taking someone else’s prescription for an appropriate  
76 medical complaint, taking by a different route or higher dose than prescribed, or taking a  
77 prescription medication to cause mind-altering affects. The most commonly misused prescription  
78 medications are those with mind-altering properties such as anti-anxiety medication, stimulants,  
79 hypnotics and opioids [2]. In 2017, an estimated 18 million Americans (6% of people over 12  
80 years of age) misused prescription medications at least once in the past year [3].

81 Nearly half of participants in a large urban methadone treatment program reported their  
82 first contact with opioids was through a doctor’s prescription for medical treatment [4]. According  
83 to the 2015 National Survey on Drug Use and Health, the most common reason for the misuse of  
84 a prescription pain reliever was in fact, to relieve pain [5]. Additionally, more than half of people  
85 who misused prescription pain relievers obtained them from friends and family [5].

86 Between 1999 and 2017, drug overdoses from prescription opioids rose from 3,442 to  
87 17,029 and the deaths from prescription opioids in combination with synthetic opioids has been  
88 steadily rising since 2014 [6]. In 2011, the Centers for Disease Control and Prevention (CDC)  
89 declared that overdoses from prescription drug abuse had become an “epidemic” and since then  
90 prescription drug misuse, including misuse of opioid medications, continues to be a significant  
91 public health issue [7].

92 In an effort to reduce the quantity of available opioid medications, many states impose  
93 prescription limits, based on CDC prescribing guidelines, on healthcare providers with the ability  
94 to prescribe scheduled drugs, but such laws vary by state [8]. Legislation to limit opioid  
95 prescriptions is relatively new. Massachusetts passed the first law in 2016 that set a 7-day supply  
96 limit for first-time opioid prescriptions. By 2020, the National Conference of State Legislatures  
97 (NCSL) reported 63 bills pending or enacted in 24 states to limit opioid prescribing [9].

98 According to NCSL, most of this legislation imposes day-limits upon new opioid  
99 prescriptions. This is generally 3-14 days, with 7 days being the average. Some states specifically  
100 set limits for minors or limit specific dosage (i.e., morphine milligram equivalents; MME). Most  
101 states differentiate between acute and chronic pain, and some states have a “professional  
102 judgement” clause which allows practitioners to override the restrictions in cases which they feel  
103 the prescription limit would be detrimental to patient care [9].

104 West Virginia has had the highest overdose mortality rate in the U.S. for a decade; in 2018  
105 the rate was 51.5 per 100,000 persons, with the vast majority of deaths involving opioids. During  
106 this same time, the national rate was 20.7 per 100,000 persons [10]. Additionally, West Virginia  
107 also has one the highest per capita rates of opioid prescriptions. In 2017, health care providers in  
108 the US wrote 58.7 opioid prescriptions per 100 persons, while in West Virginia the rate was 81.3  
109 per 100 person [11]. Even at this high per capita rate, prescription opioid dispensing was on the  
110 decline in West Virginia, with just over 31 million fewer doses of controlled medications dispensed  
111 in 2017 than 2016; of these, approximately half were opioids [12]. In addition, deaths attributed to  
112 *prescription* opioids within West Virginia decreased by 20% from 2014 to 2017 [13]. Despite the  
113 steady decline in prescription opioids, the rates of prescription-related deaths are still high in  
114 comparison to the rest of the nation [13].

115 In an effort to reduce the nonmedical use of prescription opioids further, the West Virginia  
116 legislature introduced Senate Bill (SB) 273, The Opioid Reduction Act of 2018 (*Figure 1*).

117 Figure 1: Prescription limitation language in SB 273 (Opioid Reduction Act)  
118

119 On March 27, 2018, the bill was signed and became effective June 7, 2018. This bill  
120 establishes prescribing limits for initial and subsequent opioid prescriptions by limiting ongoing  
121 chronic opioid prescriptions to 30 days' supply and first-time opioid prescriptions to 7 days' supply  
122 for surgeons and 3 days for emergency rooms and dentists, as well as establishing new opioid-  
123 related harms counselling and other requirements of prescribers. It does not apply to cancer  
124 patients, patients in hospice care, palliative care, residents of long-term care facilities, patients  
125 receiving treatment for substance use disorder, and patients receiving on-going opioid treatment  
126 as of January 1, 2018 [14].

127 The purpose of this study is to determine whether SB 273 was associated with a reduction  
128 in opioid prescribing in West Virginia, with the goal of informing future policy efforts designed  
129 to reduce opioid misuse. To this end, we examined the law's impact on multiple measures of opioid  
130 prescribing including first-time opioid prescription rates, overall opioid prescription rates, average  
131 day supply, and MME. Utilizing the state PDMP as the information source, we were able to assess  
132 the impact of the law across multiple groups of patients including both private and publicly insured  
133 patients, and uninsured patients, lending external validity to our results for broad populations of  
134 patients. In West Virginia, approximately 28% of patients are covered by Medicaid/CHIP and 24%  
135 of patients are Medicare beneficiaries [15, 16]. Seven percent are uninsured [16].

## 136 **2. Materials and Methods**

### 137 **Procedures**

138 We used an interrupted time series quasi-experimental design for state-level data to  
139 investigate opioid prescribing practices before and after the bill took effect. This methodology is  
140 useful for evaluating effectiveness of health policy changes at a population level [17].  
141 Benzodiazepine prescriptions were utilized as a control for comparison, as similar societal pressure  
142 exists to decrease benzodiazepine prescriptions, but this class of medication was not specifically  
143 addressed in SB 273.

144 After institutional review board (IRB) approval (Protocol # 1812390727), records from the  
145 West Virginia Board of Pharmacy (WVBOP) database were requested. The WVBOP database  
146 (PDMP) is an electronic database that stores data on all Schedule II-V controlled substances and  
147 opioid antagonists (and other drugs that require identification to purchase, such as  
148 pseudoephedrine) that are dispensed by practitioners to West Virginia residents, with the exception  
149 of correctional Facilities, the Indian Health Services, and tribal pharmacies. The data are required  
150 to be submitted to the WVBOP every 24 hours. RxData Track/CSAPP is the online software, run  
151 by Mahantech Corp, used by the WVBOP to track these substances. The data is stored on secure  
152 servers and all protected health information (PHI) is kept secure and confidential. The data is  
153 accessible by prescribers and dispensers for the purposes of treating their patients. Licensing  
154 boards, law enforcement, Office of the Chief Medical Examiner, and other entities have access for  
155 investigative purposes only. For this study, pediatric prescriptions as well as prescriptions written  
156 by veterinarians were excluded. Dental prescriptions were included.

157 Data requested included the overall number of opioid prescriptions, number of first-time  
158 opioid prescriptions (defined as first opioid prescription for a particular treatment or diagnosis),  
159 daily MME and prescription amounts (expressed as “day’s supply” – the terminology in the  
160 legislation) given to adults during the time period under analysis. These variables were selected

161 due to their direct relation to the required components of SB 273. The 54 weeks prior to the  
162 enactment of SB 273 (“pre-intervention”) were compared to 10 weeks between announcement and  
163 enactment of the law, and the 64 weeks after the enactment of SB 273 (“post-intervention”) in  
164 order to provide an adequate number of data points for the ARIMA analysis. We hypothesized  
165 that a significant effect would include both a significant level change (immediate change in  
166 magnitude after implementation of the law) because of the minimal expected effect lag of a policy  
167 change, and a significant slope change (change in the trend before the law as compared to after the  
168 law). An identical dataset for benzodiazepines was requested to serve as a control.

### 169 **Data Analysis**

170 Statistical analysis was done utilizing an autoregressive integrated moving average  
171 (ARIMA) interrupted time series analysis (ITS) by a trained statistician. ITS analysis is  
172 particularly well equipped to evaluate interventions [18, 19], and the ARIMA model is one of the  
173 most common interrupted time series methods [20] and widely used in health care research [17,  
174 21-23]. ARIMA was first introduced by Box and Jenkins in 1976 [24] that combined Auto  
175 Regressive (AR) model and Moving Average (MA) model to forecast stationary and non-  
176 stationary time series. In AR models, the predicted variable depends linearly on its own, previous  
177 values, and an error term. However, in MA models, the predicted variable depends linearly on the  
178 current and various past values of white noise or random shock terms. Assuming  $p$  is the number  
179 of time lags of an AR model and  $q$  is the order of an MA model, then an ARIMA process with  
180  $(p, d, q)$  order is:

$$181 Y_t = c + (\varphi_1 \hat{Y}_{t-1} + \varphi_2 \hat{Y}_{t-2} + \dots + \varphi_p \hat{Y}_{t-p}) - (\theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \dots + \theta_q \varepsilon_{t-q}) + \varepsilon_t$$

182 When  $c$  is a constant,  $X_i$  is the value of time series at time  $i$ ,  $\varphi_1, \varphi_2, \dots, \varphi_p$  are parameters of the  
183 model,  $\varepsilon_t$  is normal random noise at time  $t$ ,  $\theta_1, \theta_2, \dots, \theta_q$  are coefficients of the model, and  $\hat{Y}_t =$   
184  $\nabla^d Y_t$ . Here  $d$  time differencing ( $\nabla^d Y_t$  or  $B^d Y_t$ ) helps to produce a stationary process.

185 For each time series under study, an ARIMA model for the process over the pre-  
186 intervention period was first identified (step 1). Then, another ARIMA model with same orders  
187 was fitted to entire time series to analyze the residuals (step 2). In the final step, an ARIMAX  
188 model, the initial ARIMA model with additional regressors or exogenous variables corresponding  
189 to announcement and implementation of the legislation, was estimated for the entire time series to  
190 identify the intervention effect of both the law announcement and enactment (step 3). This  
191 approach has been previously reported [25-27]. In this study, R studio version 1.1.456 based on R  
192 version 3.5.1 was used to fit the ARIMA and ARIMAX models.

193 In the first step, the order of ARIMA was determined with autocorrelation function (ACF)  
194 and partial autocorrelation function (PACF). The model was checked for outliers; additive outliers  
195 (AO) and innovation outliers (IO) were assessed and added to the model based on procedure  
196 presented by Chang [28]. For testing adequacy, the residuals of the ARIMA models were inspected  
197 with ACF, PACF, and Ljung-Box statistics. In case of finding multiple feasible ARIMA models,  
198 the model with minimum Akaike's Information Criterion (AIC) was selected as an appropriate  
199 model.

200 In the last step, a maximum likelihood optimizer was used to estimate the selected ARIMA  
201 model with exogenous variables, an ARIMAX model. Exogenous variables in ARIMAX informed  
202 the modeling of changes following the interventions. We hypothesized the intervention impact  
203 with three functions: step function with immediate effect in mean to detect level change (1 for  
204 weeks greater or equal to intervention week; 0 otherwise), ramp function with more gradual effect

205 on the time series to detect slope change (week index after intervention for weeks greater or equal  
206 to intervention week; 0 otherwise), and pulse function to capture changes in intervention week (1  
207 for week of intervention; 0 otherwise). Statistical details are presented in Appendix 1.

208 In order to estimate the impact of intervention on the response i.e. number of opioid  
209 prescriptions, the total number of prescriptions decreased/increased because of the intervention  
210 during the post-intervention period ( $\Delta Y$ ) was estimated and compared with total number of  
211 prescriptions during that period ( $Y$ ) by  $\Delta Y/Y$ .

212 Benzodiazepine prescriptions were similarly studied as a control. The detailed modeling is  
213 provided in Appendix 1.7

214

### 215 **3. Results**

#### 216 **3.1 First-Time Opioid Prescriptions:**

217  
218 The association of the SB 273 on first-time opioid prescriptions during the time under analysis is  
219 demonstrated in *Figure 2* with the timepoints of law announcement and implementation identified  
220 by the vertical lines. There was no significant effect of SB 273 on first-time opioid prescriptions  
221 after announcing or implementing the legislation based upon this analysis. Detailed modelling is  
222 provided in Appendix 1.3.

223 Figure 2: First Time Opioid Prescriptions: Fig. 2a (top) indicates first time opioid prescriptions in  
224 the state of WV over time (in weeks). The broken vertical line indicates legislative  
225 announcement and solid vertical line indicates the legislative enactment (intervention). Red  
226 dotted line indicates fit of the mathematical model. Fig 2b (bottom) isolates the effect of the  
227 intervention.

228

#### 229 **3.2 Overall Opioid Prescriptions:**

230

231 The effect of the SB 273 on state overall opioid prescriptions during the time under analysis is  
232 demonstrated in *Figure 3* with the timepoints of law announcement and implementation identified  
233 by the vertical lines. There was a statistically significant level decrease ( $\mu = -2.98$  and  $p\text{-value} =$   
234  $0.026$ ) and slope depreciation ( $\mu = -7.39$  and  $p\text{-value} = 0.009$ ) in overall opioid prescriptions after  
235 implementing the WV legislation based on this analysis. Detailed modelling is provided in  
236 Appendix 1.4. Overall for the entire post-intervention period, it was estimated that there was a  
237 22.1% decrease in the overall number of opioid prescriptions associated with the law  
238 implementation. Detailed modelling is provided in Appendix 1.4.

239 Figure 3: Overall Opioid Prescriptions: Fig. 3a (top) indicates overall opioid prescriptions in the  
240 state of WV over time (in weeks). The broken vertical line indicates legislative announcement  
241 and solid vertical line indicates the legislative enactment (intervention). Red dotted line  
242 indicates fit of the mathematical model. Fig 3b (bottom) isolates the effect of the intervention.  
243

### 244 **3. 3 Average Day's Supply:**

245 The trend of average day supply during the time under analysis is presented in *Figure 4* with the  
246 timepoints of law announcement and implementation identified by the vertical lines. There was a  
247 notable change at timepoint 36 (in both opioid and benzodiazepine series) which will undergo  
248 additional study. There was no significant effect of SB 273 on average days' supply after  
249 announcing or implementing the legislation based on our analysis. Detailed modelling is provided  
250 in Appendix 1.5.

251 Figure 4: Average Days' Supply: Fig. 4a (top) indicates the average days' supply of opioid  
252 prescriptions in the state of WV over time (in weeks). The broken vertical line indicates  
253 legislative announcement and solid vertical line indicates the legislative enactment  
254 (intervention). Red dotted line indicates fit of the mathematical model. Fig 4b (bottom)  
255 isolates the effect of the intervention.  
256

257

258 **3.4 Average Daily MME:**

259 The association of the SB 273 on average daily MME during the time under analysis is presented  
260 in *Figure 5* with the timepoints of law announcement and implementation identified by the vertical  
261 lines. There was a statistically significant level *increase* ( $\mu= 1.30$  and  $p\text{-value}= 0.008$ ) and slope  
262 *depreciation* ( $\mu= -0.031$  and  $p\text{-value}= 0.003$ ) after implementing the legislation in average daily  
263 MME in the state of West Virginia based upon our analysis. Overall, average daily MME suddenly  
264 increased, but later followed a decreasing trend and overall was found to decrease after SB 273,  
265 however the effect size was small. The law impact on daily MME was estimated as an 0.7%  
266 *increase* considering the entire 64 weeks after the law implementation, largely due to the sudden  
267 increase in the daily MME immediately after law implementation. If only the final 25 weeks of  
268 the study are considered, a 1.1% decrease in daily MME was noted. Detailed modelling is  
269 presented in Appendix 1.6.

270 Figure 5: Average Daily Milligram Morphine Equivalents (MME): Fig. 5a (top) indicates the  
271 average daily MME of opioid prescriptions in the state of WV over time (in weeks). The broken  
272 vertical line indicates legislative announcement and solid vertical line indicates the legislative  
273 enactment (intervention). Red dotted line indicates fit of the mathematical model. Fig 5b  
274 (bottom) isolates the effect of the intervention.  
275

276

277 **3.5 Control:**

278 There was no association of the law with overall benzodiazepine prescriptions, first-time  
279 benzodiazepine prescriptions, or days' supply. Detailed modelling is presented in Appendix 1.7.

280

281 **4. Discussion**

282 Results of the current study suggest an association between SB 273 and a decrease in  
283 overall opioid prescriptions and average daily MME after legislative implementation in West

284 Virginia. There was, however, no association of the legislation with first-time opioid prescriptions  
285 or days' supply of opioid medication, and all variables were trending downward prior to  
286 implementation of SB 273. Furthermore, the daily MME initially *increased* after the law, and the  
287 overall decrease, although statistically significant, was minimal in effect size. Benzodiazepines  
288 were utilized as a control, and while the prescription numbers were similarly trending downward  
289 over the time under study, there was no association of benzodiazepine prescriptions with SB 273.

290         The verbiage of the law deserves consideration when discussing the results of this study.  
291 SB 273 sought to reduce opioid misuse and its related health impacts by setting limits for new and  
292 ongoing opioid prescriptions. This legislation limited ongoing chronic opioid prescriptions to 30  
293 days' supply, and first-time opioid prescriptions to 7 days' supply for surgeons and 3 days for  
294 emergency rooms and dentists, as well as establishing new opioid-related harms counselling and  
295 other requirements of prescribers. In spite of the specific duration limits, our analysis indicates that  
296 the days' supply of medication was not significantly affected by SB 273. Although our study  
297 cannot comment on reasons behind a lack of association of the legislation on average day supply,  
298 we can hypothesize that this finding may have been seen because prescribers were already limiting  
299 opioid prescription durations to the limits detailed in the law prior to its enactment. This is  
300 suggested because the average days' supply, although significantly higher at the beginning of the  
301 assessment period (13.9 days/prescription in March 2017) had already declined to 7.9  
302 days/prescription prior to signing of the law and continued to decline to 7.3 days/prescription prior  
303 to enactment of the law. Chua and colleagues note that opioid prescribing limits may not be  
304 effective if the imposed prescribing limits are higher than current clinical practice or patient need  
305 [29]. While we have no evidence to suggest that the imposed prescribing limits are higher than  
306 current clinical practice, it does appear that current prescribing limits closely mirror current

307 prescribing practices, which may account for the lack of significant quantitative changes in average  
308 day supply after the law.

309 In addition, it is notable that SB 273 specifically does not place a daily average MME  
310 limitation on prescribers, although it notes that the “lowest effective dose” should be utilized. In  
311 spite of this lack of specific limitations, our analysis demonstrates a change in the in the average  
312 daily MME after enactment. Further study of provider motivations would be worthwhile to  
313 determine the reasons driving this change. Similarly, SB 273 did not place restrictions upon what  
314 type of patients may receive an opioid prescription, but only directs that the prescriber must “take  
315 and document the results of a thorough medical history.” Therefore, it is difficult to attribute the  
316 decrease in overall opioid prescriptions as a result of the legislation to any specific component of  
317 the law. This may instead suggest that the legislative enactment created a general increased  
318 awareness among prescribers rather than an attempt to comply with any specific component of the  
319 legislation; however, again, specific data regarding drivers of prescriber behavior would be needed  
320 to verify this hypothesis.

321 The rationale behind opioid-limiting legislation is that decreasing exposure to opioids  
322 amongst opioid naïve patients, as well as decreasing the reservoir of available opioids in the  
323 community for misuse, may aid in curtailing the opioid epidemic. This is based upon early findings  
324 that 54% of people who misused an opioid obtained it from a friend or relative [30], with the next  
325 largest source being directly from prescribers (36%) [30]. Further correlational evidence suggests  
326 coincident trends in overdoses with medical prescription of opioids, however it is disputed whether  
327 this is a causal relationship and whether previously seen statistics from the “first wave” of the  
328 opioid epidemic are still relevant when illicit opioids are currently more prominent sources of  
329 adverse events [31]. However, while there is no definitive evidence as to the source of diverted or

330 misused opioids, the study of diversion of medically prescribed opioids is most robust in the  
331 acute/first-time opioid prescription phase [30]. In a meta-analysis of multiple studies, Bicket and  
332 colleagues found that 67-92% of patients did not use their full opioid prescriptions after surgery,  
333 with as few as 9% of patients disposing of them properly [30]. In contrast, given the measures  
334 already in place for patients on chronic opioid medications (urine drugs screens, pill counts, etc.)  
335 which are not implemented for patients receiving short term opioid prescriptions, it is arguable  
336 whether decreasing the ongoing opioid prescription number without decreasing the first-time  
337 opioid prescription number (as seen in our study) will have any measurable effect on opioid misuse  
338 or diversion. The results of our study do not specifically assess either opioid misuse or diversion,  
339 and therefore no conclusions about the effect of this legislation on these metrics can be drawn.

340           Importantly, the decreased overall prescription number without a corresponding decrease  
341 in new opioid prescriptions seem to indicate that patients with chronic pain conditions may be  
342 more significantly affected by these legislation effects. This raises concerns of inadequate pain  
343 control, or “forced tapering” amongst these patients, particularly given recent concerns that these  
344 phenomena may drive illicit use [32]. Confirmation of this finding through clinical data and patient  
345 interviews would be helpful to characterize the impact of such legislation on chronic pain patients  
346 and any unintended consequences regarding transitions to illicit opioid use.

347           In contrast to other policy efforts which have undergone study, West Virginia SB 273 did  
348 not have an exception for “professional judgement,” which allows prescribers to override the limits  
349 if they feel it is medically required. Agarwal and colleagues [33] have previously postulated that  
350 exceptions for “professional judgement” may account for the lack of effect, or minimal effect, of  
351 similar laws in other states; concordantly, we found an association in the absence of such an  
352 exception within this state specific legislation, which may support that assertion. Greene and

353 colleagues [34] have similarly noted anecdotal evidence that physicians were “getting around”  
354 state level prescription limits by writing and back-dating multiple prescriptions, however our data  
355 does not support that theory in West Virginia given the continuing decrease in overall number of  
356 prescriptions.

357 Finally, unlike prior studies in other states, we included the law announcement in our  
358 analysis in order to capture anticipatory effects on prescription habits. We found no anticipatory  
359 effect of the law announcement for any variable. However, our methods do not allow us to discern  
360 whether this was due to lack of knowledge/dissemination of the law prior to enactment, or because  
361 anticipation of the legislative enactment was not a strong enough driver of prescriber behavior.  
362 Accordingly, further study of prescriber-level drivers of prescribing behavior may be warranted.

363 SB 273 is one of several state-level legislative efforts in recent years to curtail opioid  
364 prescribing, with 26 states having enacted these laws by 2017 [35] and 31 states overall having  
365 enacted a policy of this type by 2019 [33]. Both Massachusetts and Connecticut instituted 7-day  
366 limits for initial opioid prescriptions, with exceptions for chronic, cancer-related, palliative care-  
367 related pain similar to the West Virginia legislation; and a “professional judgement” override in  
368 contrast to the West Virginia legislation [33]. Florida legislation imposed a more stringent  
369 requirement than in other states (3-day limit) [36]. Previous research into the effects of such laws  
370 have been mixed. Agarwal and colleagues [33] found variable association of state-level opioid  
371 prescribing limits with post-operative opioid prescribing in Massachusetts and Connecticut, but  
372 even when a decrease was observed, the magnitude was small. In contrast, study of similar  
373 legislation in Rhode Island and Florida demonstrated significant decreases in post-surgical opioid  
374 prescribing specifically after state-level opioid prescription limits [36-38].

375           This conflict in results may be explained by differences in methodology. In Potnuru’s  
376 study, pre-intervention indicators of opioid use were compared with post-intervention indicators  
377 but there was no accounting for pre-intervention trends, which means the effect reported may have  
378 been similar to the downward trend we see in our own data rather than directly attributable to the  
379 legislative action [38]. A similar methodology was employed in Reid’s [37] study, leading to  
380 similar lack of accounting for pre-intervention trends. In Yenerall and McPheeter’s [39] study,  
381 the population under study was a priori defined as “patients currently receiving long-term opioid  
382 treatment and most likely to be directly affected by the law” and they limited their analysis to  
383 patients who “had at least one prescription with a days’ supply exceeding 30-days in the pre-policy  
384 period.” Therefore, since they were assessing the effect of a law that limited the days’ supply of  
385 chronic opioids to 30 days, it is unsurprising that they discovered an effect of the legislation in  
386 their analysis of this highly selected patient population specifically, which according to their own  
387 data is not representative of the majority of prescriptions in the state.

388           Our data demonstrates the importance of methodology in this type of analysis. If serial  
389 correlation and pre-intervention trends are ignored and a two sample t-test comparison is made  
390 before and after law enactment (Appendix 1.1), a significant decrease in all variables except daily  
391 MME was seen after implementation of the law when compared to before implementation;  
392 however, when accounting for pre-intervention trends, seasonality, autocorrelation, etc., no lasting  
393 effect of the legislation was seen on first-time opioid prescription and average day supply; instead  
394 the only significant effects were on average daily MME and overall opioid prescriptions.  
395 Therefore, we recommend that further analysis of such legislative efforts utilize an interrupted  
396 time series methodology.

397            Interrupted time series analysis depends upon there being no other relevant events on the  
398 date of the intervention which may act as confounders. Accordingly, it is relevant to note that the  
399 day of enactment of SB 273 (June 7, 2018), the White House also announced a new advertising  
400 campaign “The Truth About Opioids” to attempt to curtail opioid use disorder. This advertising  
401 campaign is directly relevant to the topic of opioid prescribing and enjoyed widespread exposure  
402 in a variety of media, ultimately winning an Emmy Award. This could have accounted for some  
403 of the change seen in our study. The decrease in general measures of opioid prescribing rather  
404 than measures directly addressed by the legislation further emphasize this possibility. A further  
405 possible confounder is that the PDMP is based upon how the prescription is filled rather than how  
406 it is written. This introduces the possibility that while a prescriber may not comply with the law  
407 or may have written an increased days’ supply, the pharmacist may refuse to fill the prescription  
408 as written and instead fill it as the law requires. However again, since no change was demonstrated  
409 in average day supply this would only be relevant if prescribers wrote for more opioids after the  
410 law, not less, which is not suggested by the trends.

411            Our study has several additional limitations. Working with the PDMP data in West  
412 Virginia we are able to capture prescribing data for prescriptions written and filled within the state,  
413 but may have lost data for prescriptions not filled in West Virginia. Several high-volume medical  
414 centers are located on state borders, making this limitation potentially relevant. Furthermore, our  
415 study does not include clinical data regarding patient diagnoses, re-admissions due to pain, etc.  
416 This is relevant because similar studies have demonstrated opioid-related harms in relation to such  
417 legislation.

418            Further work exploring the specific methods of dissemination and implementation of SB  
419 273 may be relevant to compare West Virginia to other states in which prescribing limits have had

420 varying effects. Similarly, additional assessment of the clinical effect of the overall trends of  
421 opioid prescribing in West Virginia are warranted given the decreasing trends seen through the  
422 assessment period. While prescribing limits have been attributed by patients and providers as the  
423 source of unintended consequences due to decreased prescribing of opioid medications (34)  
424 (Greene et al., 2018), verification of this through rigorous scientific means is warranted.

## 425 **5. Conclusion**

426 Results of the current study suggest an association of SB 273 with a 22.1% decrease in  
427 overall opioid prescriptions across 64 weeks after the intervention, as well as a small change in  
428 daily average MME associated with the legislation enactment, but no change in first-time opioid  
429 prescriptions or days' supply. There was no change in any metric resulting from announcement of  
430 the legislation. Downward trends in first-time opioid prescriptions and average day supply were  
431 seen throughout study, but were not associated with SB 273, and further study is indicated to  
432 understand drivers behind this trend, as well as unintended consequences. Our data seem to  
433 indicate a decrease in ongoing opioid prescriptions rather than new prescriptions, and the effect of  
434 this finding on patients with chronic pain conditions is potentially concerning and should be  
435 investigated. Finally, it is important to note that the effect of this legislation on diverted or misused  
436 opioids was not assessed in this study.

## 437 **Abbreviations**

438 ACF- autocorrelation function  
439 AIC- Akaike's Information Criterion  
440 AO- additive outliers  
441 AR- auto regressive  
442 ARIMA - autoregressive integrated moving average  
443 ARIMAX- ARIMA model with exogenous variables  
444 CDC- Centers for Disease Control and Prevention

445 IO- innovation outliers  
446 IRB - institutional review board  
447 ITS- interrupted time series analysis  
448 MA- moving average  
449 MME - morphine milligram equivalents  
450 NCSL - National Conference of State Legislatures.  
451 PACF- partial autocorrelation function  
452 PDMP - prescription Drug Monitoring Program  
453 PHI - protected health information  
454 SB 237- The Opioid Reduction Act (Senate Bill 273)  
455 WVBOP – West Virginia Board of Pharmacy

456 **Declarations**

457 **Ethics approval and consent to participate**

458 The Institutional Review Board of West Virginia University approved this study.

459 **Consent for publication**

460 Not applicable

461 **Availability of data and materials**

462 Data used for this study can be accessed upon request from the Principal Investigator (Dr. Cara  
463 Sedney) at [csedney@hsc.wvu.edu](mailto:csedney@hsc.wvu.edu)

464 **Competing interests**

465 The authors declare that they have no competing interests.

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#### 474 **Authors' Contributions**

475 This study was led by CS and TH who were key contributors to study design, analysis, drafting  
476 and writing of the article. MK provided statistical support and analysis of data. RP contributed to  
477 drafting and writing of the article and provided expert input into study design. PD assisted with  
478 data acquisition and drafting of the article as well as administrative support for the study. NW  
479 assisted with data acquisition and analysis. All authors have read and approved the version to be  
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# Figures

## **§16-54-4. Opioid prescription limitations.**

When issuing a prescription for an opioid to an adult patient seeking treatment in an emergency room for outpatient use, a health care practitioner may not issue a prescription for more than a four-day supply.

(b) When issuing a prescription for an opioid to an adult patient seeking treatment in an urgent care facility setting for outpatient use, a health care practitioner may not issue a prescription for more than a four-day supply: *Provided*, That an additional dosing for up to no more than a seven-day supply may be permitted, but only if the medical rationale for more than a four-day supply is documented in the medical record.

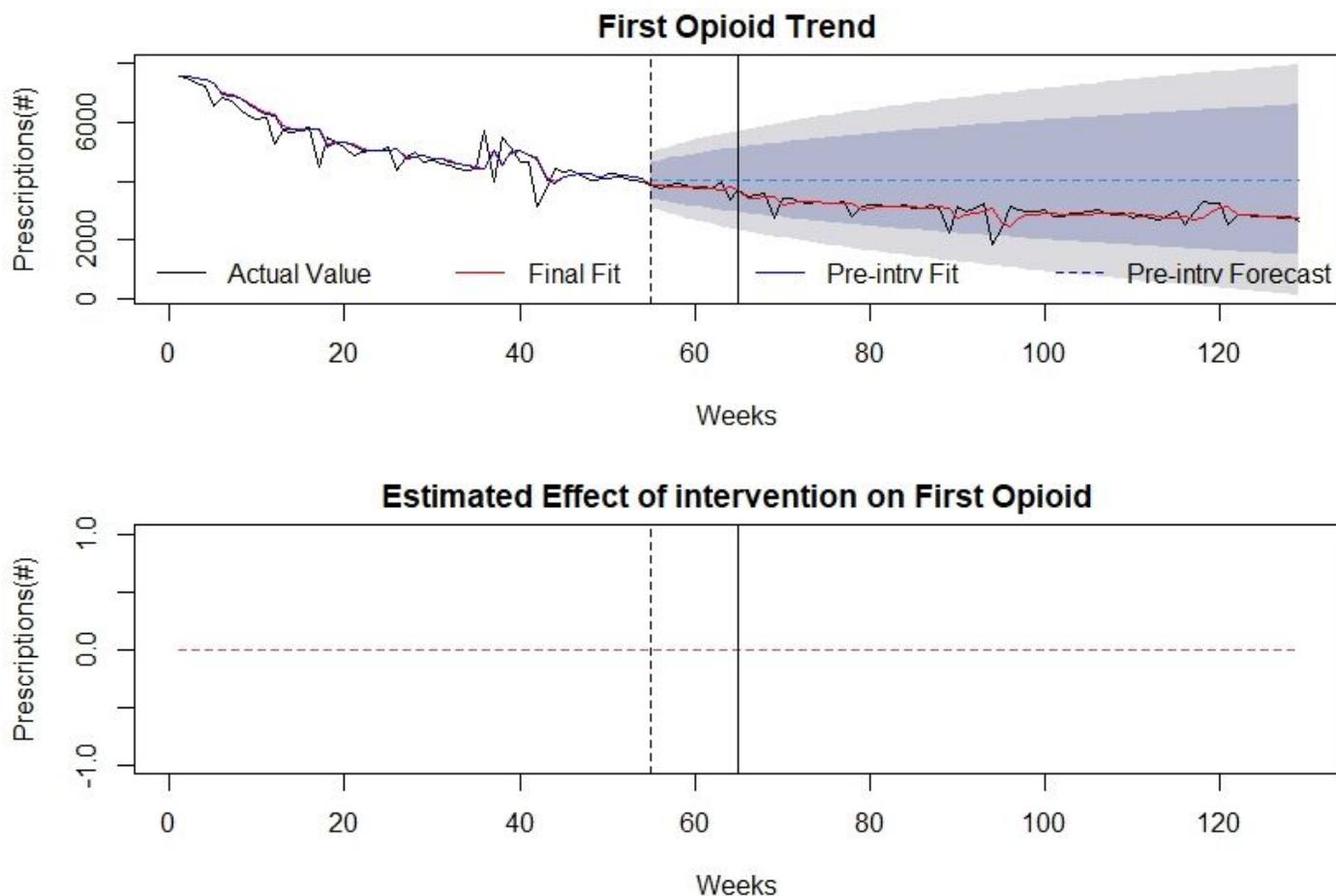
(c) A health care practitioner may not issue an opioid prescription to a minor for more than a three-day supply and shall discuss with the parent or guardian of the minor the risks associated with opioid use and the reasons why the prescription is necessary.

(d) A dentist or an optometrist may not issue an opioid prescription for more than a three-day supply at any time.

(e) A practitioner may not issue an initial opioid prescription for more than a seven-day supply. The prescription shall be for the lowest effective dose which in the medical judgement of the practitioner would be the best course of treatment for this patient and his or her condition.

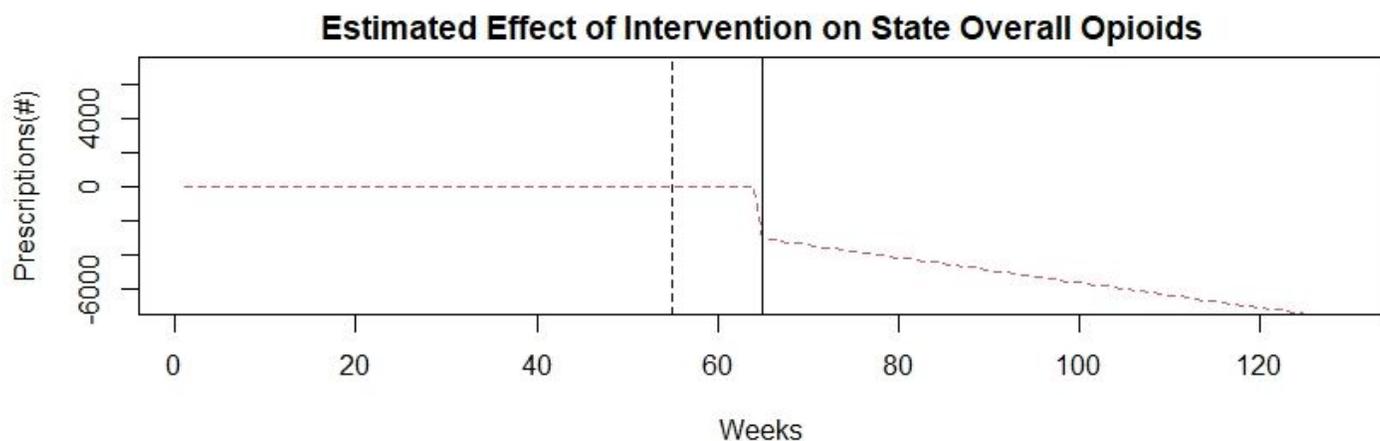
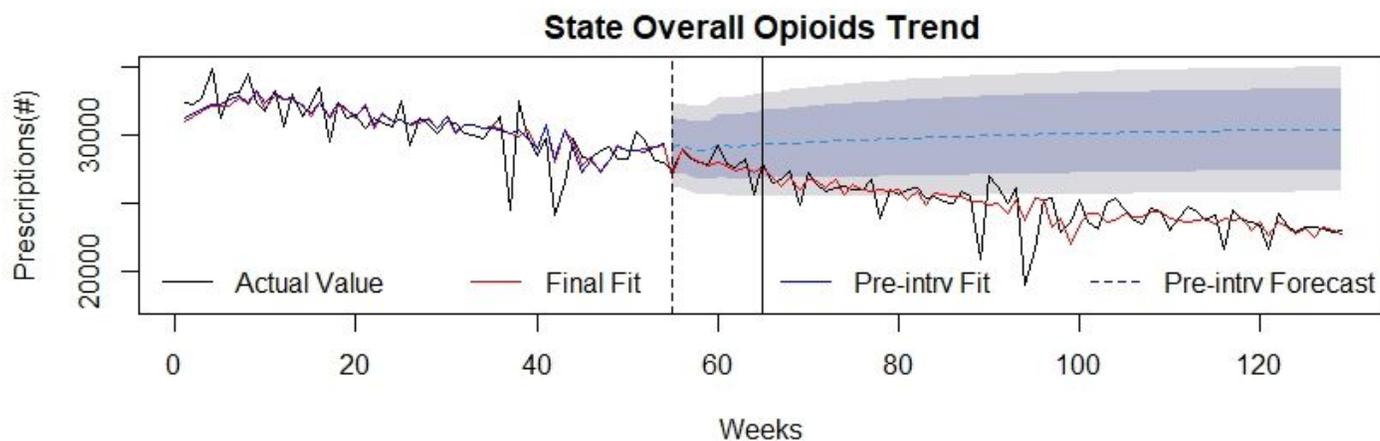
Figure 1

Prescription limitation language in SB 273 (Opioid Reduction Act)



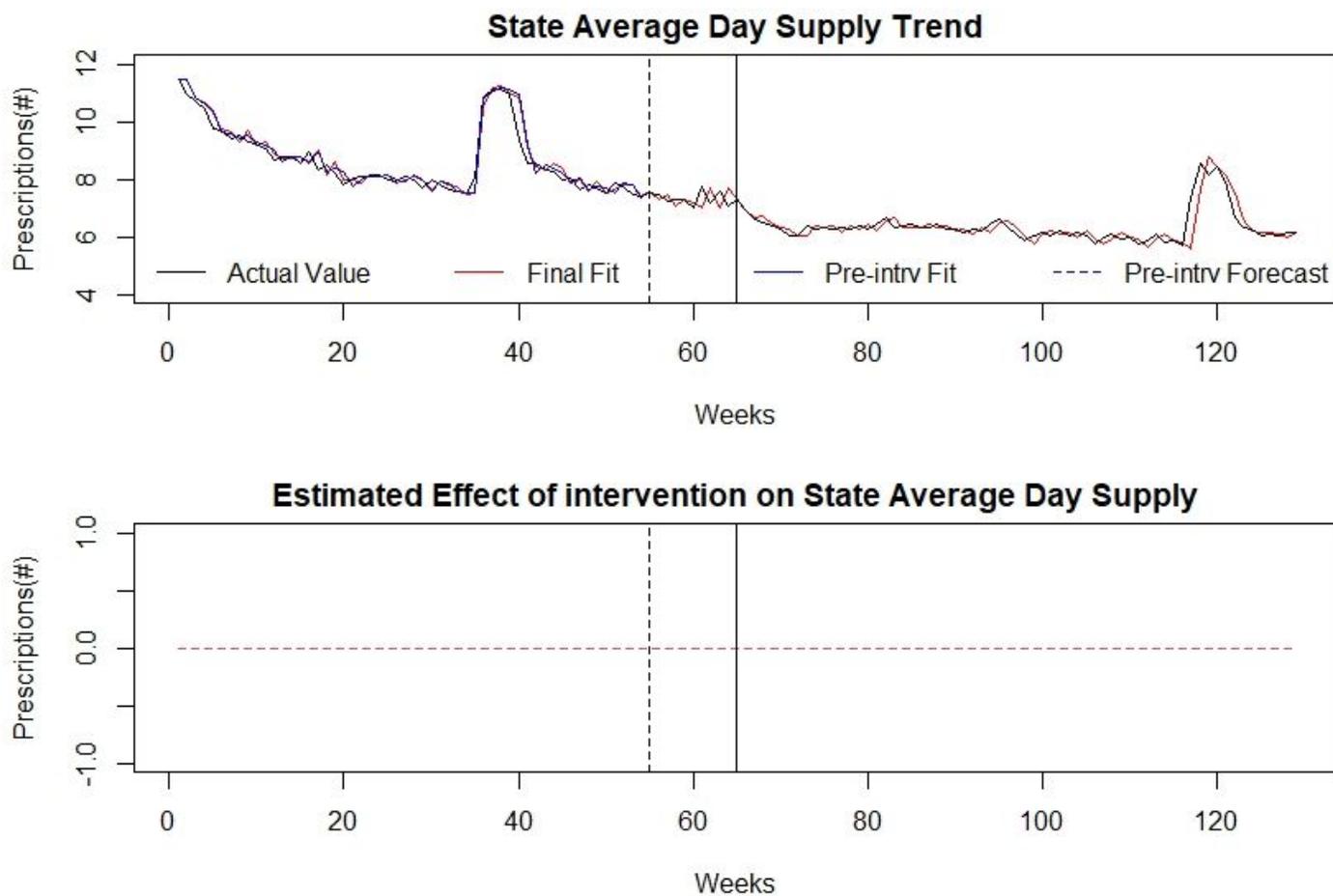
**Figure 2**

First Time Opioid Prescriptions: Fig. 2a (top) indicates first time opioid prescriptions in the state of WV over time (in weeks). The broken vertical line indicates legislative announcement and solid vertical line indicates the legislative enactment (intervention). Red dotted line indicates fit of the mathematical model. Fig 2b (bottom) isolates the effect of the intervention.



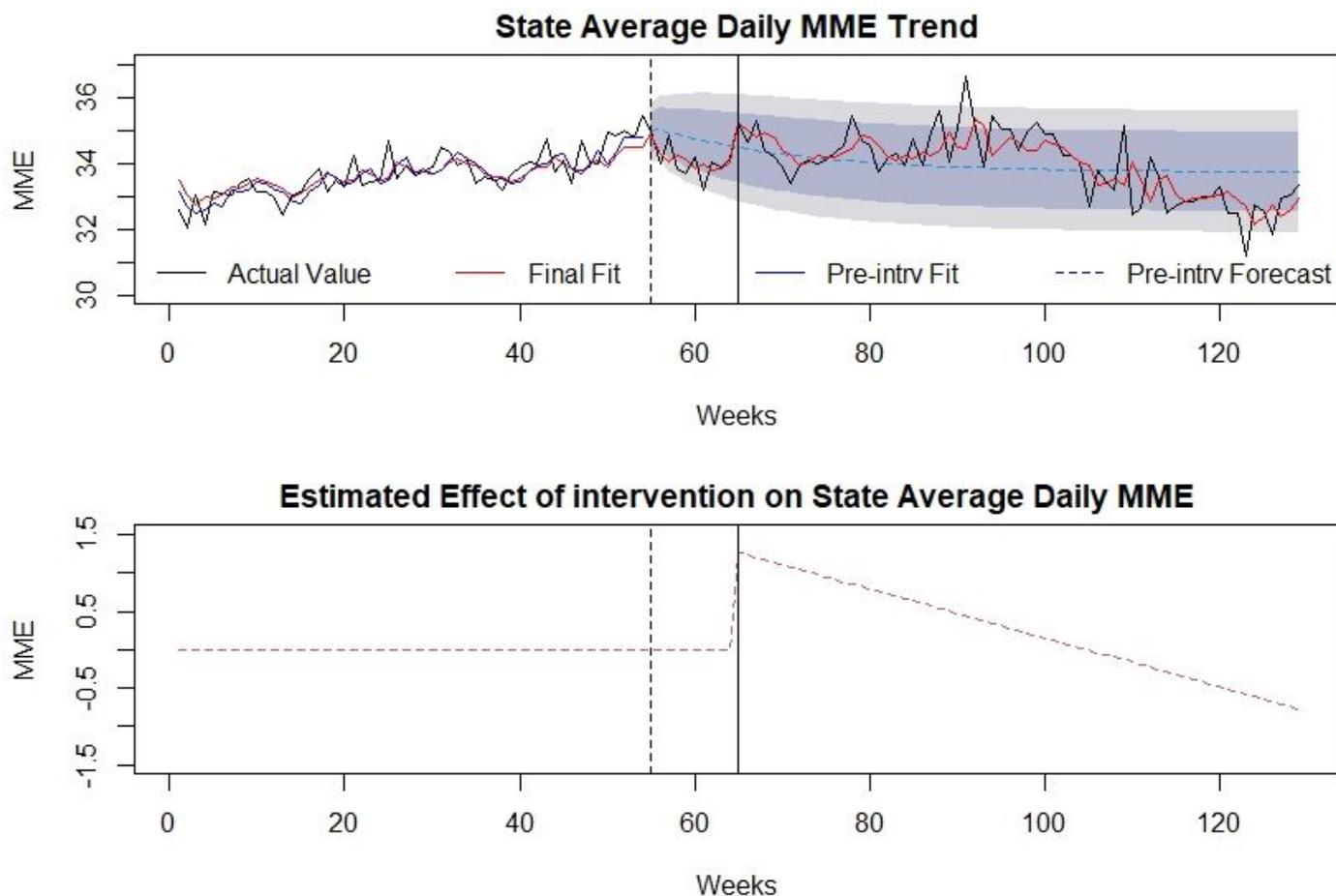
**Figure 3**

Overall Opioid Prescriptions: Fig. 3a (top) indicates overall opioid prescriptions in the state of WV over time (in weeks). The broken vertical line indicates legislative announcement and solid vertical line indicates the legislative enactment (intervention). Red dotted line indicates fit of the mathematical model. Fig 3b (bottom) isolates the effect of the intervention.



**Figure 4**

Average Days' Supply: Fig. 4a (top) indicates the average days' supply of opioid prescriptions in the state of WV over time (in weeks). The broken vertical line indicates legislative announcement and solid vertical line indicates the legislative enactment (intervention). Red dotted line indicates fit of the mathematical model. Fig 4b (bottom) isolates the effect of the intervention.



**Figure 5**

Average Daily Milligram Morphine Equivalents (MME): Fig. 5a (top) indicates the average daily MME of opioid prescriptions in the state of WV over time (in weeks). The broken vertical line indicates legislative announcement and solid vertical line indicates the legislative enactment (intervention). Red dotted line indicates fit of the mathematical model. Fig 5b (bottom) isolates the effect of the intervention.

## Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [AdditionalFileAppendix.docx](#)