Drug Decriminalization and Drug Overdose: A Case Study of Oregon's Measure 110

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Abstract

In 2021, the United States surpassed 100,000 annual drug overdose deaths. In Oregon, Measure 110 decriminalized drug use on 1 February 2021, making Oregon the first US State to decriminalize drug use. This paper studies drug decriminalization in Oregon using the Synthetic Control Method. State-level monthly unintentional drug overdose death data based on death certificates is obtained from the CDC. Comparing Oregon to a synthetic doppelganger constructed from a convex combination of other states, the results indicate that Measure 110 increased overdose deaths by 528 in the 20 months from March 2021 to October 2022.

Keywords*:* Drug Decriminalization, Drug Overdose Deaths, Measure 110, Substance Use Treatment, Synthetic Control Method

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1. Introduction

The United States saw a sobering escalation in drug-related fatalities in 2021, reaching an annual toll of over 100,000 drug overdose deaths (Netherland et al, 2022). This grim milestone marked more than a tripling of such deaths since 1990 and a disturbing 29% rise between 2019 and 2020, following a 4% increment from 2018 to 2019 (Towles, 2022). Moreover, opioids were implicated in seven out of every ten overdose deaths in this period (NCDAS, 2023). This escalating crisis has instigated a flurry of economic research examining the potential impacts of drug decriminalization on drug demand, supply, and public health outcomes, such as overdose fatalities. However, the relationship among the decriminalization of drug use, health interventions, and overdose deaths has been found to be multifaceted, leading to a spectrum of findings in the literature.

Most existing studies focus on marijuana decriminalization at the US state level, generating mixed results, and lack an in-depth exploration of the broader implications of drug decriminalization. For instance, research from Western Australia suggests that marijuana decriminalization led to an uptick in use among minors in the five years following decriminalization (Williams and Bretteville-Jensen, 2014). The ongoing overdose epidemic has reignited the discussion around drug decriminalization as a potential policy solution, especially considering the wide-ranging economic implications of such a measure, such as changes in healthcare expenditures, criminal justice costs, tax revenues, and public health outcomes. Yet, the empirical evidence examining the causal effects of broad non-marijuana decriminalization on drug overdoses is woefully sparse (Félix et al., 2017; Spencer, 2022).

This paper seeks to fill this gap by examining the potential causal impact of Oregon's Measure 110 on drug overdose deaths. Enacted in February 2021 following a November 2020 vote, Measure 110 provides a unique opportunity to study the effects of an isolated and sudden implementation of drug decriminalization on public health outcomes and the lives of people who use drugs (PWUD). The consequences of drug decriminalization on drug use and overdose deaths is a matter of critical importance for both researchers and policymakers, and Oregon’s Measure 110 offers a prime case study.

Current studies on comprehensive drug decriminalization are often limited in their scope and challenged by difficulties in drawing causal inferences due to the absence of comparable groups. In an effort to overcome these limitations, this paper leverages a natural experiment design to estimate the causal impact of drug decriminalization. The unusual circumstance of a US state implementing drug decriminalization through direct citizen action, rather than traditional legislative channels, provides an invaluable context for studying its causal impacts, particularly when juxtaposed with the broader nation.

The exploration of this state-level policy shift employs the Synthetic Control Method (SCM), an approach first proposed by Abadie and Gardeazabal (2003) and later refined by Abadie et al. (2010). The empirical analysis in this paper is guided by the methodological frameworks set out by Félix et al. (2017) and Spencer (2022). Data for unintentional drug overdose fatalities, derived from death certificates, is obtained from the CDC's WONDER system, spanning the period from January 2018 through September 2022.

Preliminary findings point towards an additional 528 overdose deaths in Oregon in the 20 months from March 2021 to October 2022, a 40% rise when compared to the synthetic Oregon estimate for the same period. The statistical significance of the treatment effect was ascertained via in-space placebo studies. Additionally, a comparison of the post/pre-Measure 110 MSPE ratios to Oregon's across states in the donor pool, as if they had received the treatment in February 2021, suggests a likelihood of roughly 2.5% for obtaining a ratio as large as Oregon's by chance. Multiple robustness checks, such as bias-correction synthetic control, leave-one-out-robustness, and in-time placebo tests, did not lead to substantial changes in the results.

The remainder of the paper is structured as follows: Section 2 describes Measure 110 and previous literature, Section 3 describes the data, Section 4 explains the empirical strategy, Section 5 documents the results, and Section 6 concludes.

2. Measure 110 and Background

2.1 Measure 110

In the November 2020 elections, Oregon voters passed Measure 110, also known as The Drug Addiction Treatment and Recovery Act. This ballot measure became law on 1 February 2021, making Oregon the first US state to decriminalize the possession of small amounts of all drugs (Oregon Legislative Policy and Research Office, 2020; Towles, 2022). Measure 110 reclassifies those small possession charges to a class E civil violation, associated with a $100 fine that can be waived if the charged person contacts a helpline or recovery center about other treatments (Oregon Legislative Policy and Research Office, 2020; Towles, 2022). In addition to reclassifying possession charges, Measure 110 establishes funding for an addiction and drug treatment program in Oregon through use of state Marijuana taxes and savings from reduced spending on law enforcement (Oregon Legislative Policy and Research Office, 2020; Towles, 2022). The addiction treatment services include funding for Behavioral Health Resource Networks which provide intensive case management, linkage to care and services, peer support, and mobile or virtual outreach.

Opponents to Measure 110 argue that criminality serves to reduce the incentive to do drugs, which can be associated with various adverse health effects such as overdose deaths, HIV and Hepatitis C infections, heart value infections, skin-grafts, domestic violence, suicide, loss of child-custody, and social isolation (Towles, 2022). Addiction reduces cognitive ability, which can be in turn associated with many damaging impacts such as increased rates of other crimes.

2.2 Related Literature

The literature on drivers of drug use reaches many different fields and studies various types of factors that can contribute to drug use. An influential view was posited by Becker and Murphy (1988) in their seminal work on the theory of rational addiction. Considering PWUD as rational consumers maximizing utility over an intertemporal budget constraint, Becker and Murphy (1988) find that drug use is rational when viewed from the preferences of an addict weighing short term pleasure against long term downsides. Past experience with drug use would increase the preference for drug use, altering the rational decision. A decade later, Saffer and Chaloupka (1999) empirically study the demand for illicit drugs and find that increases in an illegal drug's price can decrease its demand as well as that decriminalization of cannabis can increase cannabis demand. Established economic research demonstrates drug use as consumer behavior responding to preferences and economic incentives.

Beyond individual reasons for drug use, the broader and more recent literature emphasize three additional categories of factors that drive drug use: relational, societal, and contextual. Galea, Nandi, and Vlahov (2004) emphasize the social epidemiology of substance use, arguing that substance use patterns are significantly influenced by sociodemographic and environmental factors, such as socioeconomic status and the social environment in which individuals live. Research in recent years has turned its attention more towards the growing health priority of substance use among young people (Degenhardt et al., 2016). When someone uses substances at a young age, it can lead to a higher likelihood of developing substance use disorders later in life (Degenhardt et al., 2016). The onset of substance use appears largely influenced by social factors such as peer influence and family background (Degenhardt et al., 2016). Which such wide-ranging factors contributing to drug use, many different responses to substance use have been used or proposed throughout globe.

Oregon's Measure 110 is not the first policy aimed at reducing drug-related harm and overdose deaths in the United States. In recent years, addressing the overdose epidemic, several states have implemented policies to reduce opioid abuse and overdose deaths, such as prescription drug monitoring programs and naloxone access laws. Research has shown that these policies have been effective in reducing opioid-related deaths (Delcher et al., 2015; Patrick et al., 2016; Smart et al., 2021). PDMPs are electronic databases that track controlled substance prescriptions in a state. The goal of PDMPs is to prevent over-prescribing and doctor shopping, which drive the opioid epidemic.

Research also shows that syringe service programs (SEPs) can reduce HIV and Hepatitis C infection as well as overdose death, without increasing drug use or crime (Jarlais et al., 2015; Strathdee et al., 2006). Although, there is evidence that focusing accessibility in urban areas may have left rural and suburban people behind (Jarlais et al., 2015). Moreover, recent analysis using administrative data found that SEPs may increase opioid-related deaths, especially in rural areas and areas that suffer from fentanyl use before the implementation of the SEP (Packham, 2022). Harm reduction policies, which do not directly work to reduce drug use but rather associated harms, have been shown to be effective at reducing health issues of drug use while not increasing drug use (Strathdee et al., 2006; Delcher et al., 2015; Jarlais et al., 2015; Patrick et al., 2016; Smart et al., 2021; Packham, 2022).

Various types of drug treatment policies have been attempted which work to stop or end drug usage in the patient entirely. Methadone maintenance therapy is more effective in reducing drug use and mortality than no opioid replacement therapy (Mattick et al., 2009). Other policies have been implemented such as Good Samaritan laws, but due to longstanding systemic racism and distrust some policies such as these may fail to garner the trust desired from PWUDs (Pamplin, et al., 2023). These drug treatment techniques can inform my analysis of Measure 110.

Medical marijuana has seen a quick and broad rise in its legality in the US, and a large literature exists examining its impacts. Analyzing survey data to investigate marijuana decriminalization's impact on youth attitudes in California 2007-2013 suggest that marijuana decriminalization increased 12th graders in 2012 and 2013's use of marijuana as well as reduced their disapproval rates of marijuana (Miech, et al., 2009). On the other hand, using a difference-in-differences framework to analyze CDC survey data revealed that medical marijuana legalization did not impact youth consumption rates (Choo, et. al., 2014). Although economic theory implies that decriminalization would change the incentives around drug use—leading to an increase in drug use after decriminalization—results from marijuana decriminalization and medical legalization show that decriminalization may not necessarily increase use.

Internationally, Portugal represents a model for drug decriminalization policies. In 2001, Portugal decriminalized the possession of all drugs while also redirecting funding from criminal justice to healthcare services—increasing treatment access. Since then, the country has seen a significant decrease in drug-related deaths and HIV infections and an increase in the number of people seeking treatment for addiction (Greenwald, 2009). Surprisingly, few studies have been conducted to estimate causal impacts of broad drug decriminalization. Félix et al. (2017) studied Portugal using the SCM and found that their decriminalization decreased drug overdose deaths.

Both Oregon and Portugal decriminalized drugs but did not depenalize drugs, with Portugal's 2001 reform requiring people who use drugs to face "Commissions for Dissuasions of Drug Addiction" which dictate treatment requirements, warnings, and fines (Greenwald, 2009). In the case of Portugal, treatment is considered the primary responses with fines being seen as a last resort tool used only on those deemed addicts (Greenwald, 2009). Since decriminalization, Portugal has seen crime and court costs decrease but treatment and other prevention costs increase (Félix, et al., 2017). Both Oregon's and Portugal's decriminalization make no

distinction for public or private consumption, or between different specific drugs (Greenwald, 2009).

A working paper by Spencer (2022) found that Measure 110 increased overdose deaths in Oregon, but his analysis is limited to the first 11 months of Measure 110's implementation. Specifically, Spencer estimates that Measure 110 caused an increase in 206 overdose deaths which is a 27% increase over the synthetic control. I agree with his methodology choice of the SCM to build a synthetic Oregon from data on the other 48 states, besides Washington since it temporarily decriminalized drugs in 2021, and DC. This method has some advantages over the difference in differences technique which falls victim to endogeneity of treatment as well as serial autocorrelation leading to underestimated standard errors (Bertrand, et al., 2004). My paper is different from Spencer's working paper because I consider a longer time period of data.

3. Empirical Methodology

To determine the impact of Measure 110 on drug overdose deaths, this paper employs the SCM, as pioneered by Abadie and Gardeazabal (2003) and Abadie et al. (2010). A fundamental challenge in policy analysis is the inability to observe alternative outcomes under different policies. In the context of Measure 110, this implies that we cannot observe Oregon in a scenario where Measure 110 was not enacted. However, the SCM allows us to construct a "synthetic Oregon" using data from other states, which can serve as a counterfactual to compare against the actual Oregon. The formal model in this paper closely aligns with those presented in Félix et al. (2017) and Spencer (2022).

With Y_{it}^N as overdose deaths in state i during month t without decriminalization, and T_0 as pre-treatment months, I define decriminalization effect, $\alpha_{it} = Y_{it}^I - Y_{it}^N$ (1), where Y_{it}^I represents deaths with decriminalization from the first treatment period $T_0 + 1$ to T, for states $i = 1, \dots, J + 1$ and months $t = 1, \dots, T$. Using D_{it} as an indicator for state i's treatment during month t, the observed outcome is $Y_{it} = Y_{it}^N + \alpha_{it} D_{it}$ (2). Identifying Oregon as state $i = 1$, I aim to estimate the sequence $(\alpha_{1T_0+1}, \alpha_{1T_0+2}, \dots, \alpha_{1T})$, representing the treatment effect for each post-intervention month.

To estimate these effects, we observe Y_{it}^{I} and estimate the counterfactual Y_{it}^{N} for Oregon in $t > T_0$. Y_{it}^{N} is estimated using a weighted average of monthly overdose deaths in all other US States and DC, excluding Washington: $\hat{Y}_{1t}^{N} = \sum_{j=2}^{J+1} w_j^* Y_{jt}$ (3), where w_j^* is the optimal weight of state j for synthetic Oregon. Non-negative weights that sum to one are chosen to optimize the pre-intervention mean square prediction error (MSPE):

$$\sum_{t \in \tau_0} \left(Y_{1t} - w_2(V) Y_{2t} - \cdots - w_{J+1}(V) Y_{J+1t}\right)^2 \quad (4)$$

for Oregon, where V optimally weights the importance of matching the predictor variables in X and τ_0 . Various predictor variables will be used to match the donor states to Oregon, these specific variables will be noted in the next section. Pre-treatment MSPE is used to measure the fit of the synthetic, and post-treatment MSPE is used to measure the difference between the real unit and the estimated synthetic counterpart. This paper will follow a common approach in the SCM literature for estimating p-values using placebo tests and the ratio of post/pre-MSPE, with a larger than one suggesting a significant impact. The full equation of interest,

$$\hat{\alpha}_{1T} = Y_{1T} - \hat{Y}_{1t}^{N} = Y_{1t} - \sum_{j=2}^{J+1} w_j^* Y_{jt} \quad (5),$$

is estimated for each post-intervention period. This estimated treatment effect reveals the difference in overdose deaths in Oregon after Measure 110 compared to synthetic Oregon, offering empirical evidence of Measure 110's impact on drug deaths.

The SCM comes with several underlying assumptions and potential issues, which may affect the validity of the results. The first critical assumption of this model is that Measure 110 has no effect prior to its implementation. This assumption, known as the *no anticipation effect*, posits that potential changes in behavior anticipating the implementation of the measure would not influence overdose death rates. If, however, individuals or institutions altered their behavior in anticipation of the law, this could bias the results. For example, individuals might change their drug use patterns or healthcare providers might alter their prescribing habits in anticipation of the policy change, and this could introduce an anticipation effect bias. A second important assumption of this model is that Measure 110 does not impact overdose deaths in other states used as controls. This assumption, often referred to as the *no spillover effect* assumption, suggests that the policy change in Oregon would not affect drug overdose rates in other states.

Yet, the potential for policy diffusion or the influence of policy changes in one state on the behaviors of individuals in neighboring states could challenge the validity of this assumption. For instance, if residents of neighboring states travel to Oregon to take advantage of the policy change, it may indirectly affect overdose rates in those neighboring states, violating this assumption and potentially leading to biased results. However, considering the outcome under study is unintentional drug overdose deaths, I would not anticipate this assumption to be violated.

A third potential issue with the SCM relates to the number of pre-treatment periods. The accuracy of the synthetic control in predicting what would have happened in the absence of the treatment heavily relies on the number of pre-treatment periods available. If the pre-treatment periods are insufficient, it may limit the synthetic control's ability to accurately track the trajectory of the real Oregon, hence compromising the reliability of the counterfactual. The fourth challenge concerns the number of post-treatment periods. If there aren't enough post-treatment periods, it may limit our understanding of the policy's long-term impact. For instance, if the effects of Measure 110 emerged gradually over time or changed in magnitude or direction, a limited number of post-treatment periods may fail to capture these evolving effects. Lastly, SCM exclusively uses interpolation, thereby restricting the synthetic control to be a convex combination of the units in the donor pool. This constraint could create a bias in the results if the synthetic control does not perfectly match the treated unit. That is, if no combination of control units closely resembles Oregon in the pre-treatment period, the synthetic control may be a poor counterfactual, leading to biased estimates of the treatment effect.

To address these limitations and test the robustness of the results, several analyses have been conducted, including in-space and in-time placebo studies, leave-one-out robustness checks, and matching variable sensitivity analysis. Each of these analyses help validate the main findings and check the assumptions underlying the SCM.

4. Data

4.1 Unintentional Drug Overdose Death Data

To investigate the impact of Measure 110 on overdose deaths, this study requires data on accidental drug overdose deaths in Oregon both before and after the implementation of Measure

110. The data should be in panel format to facilitate the estimation of a synthetic control, which involves multiple pre-treatment periods and non-treated states in addition to Oregon post-treatment. For this analysis, the model utilizes data from the CDC's Provisional Multiple Cause of Death Data, covering the period from January 2018 to October 2022. These monthly data are categorized by the state of occurrence, including Washington D.C. However, Washington state is mostly excluded from the analysis due to its temporary decriminalization of drug possession in 2021, mandated by a court order.

This state-level mortality data is derived from death certificates and includes one underlying cause of death, with the possibility of listing multiple additional causes. The study focuses specifically on deaths attributed to unintentional drug overdose, excluding those classified as suicidal, homicidal, or undetermined drug overdose deaths. For confidentiality purposes, if a particular state-month combination has fewer than 10 overdose deaths, the count is suppressed. States with suppressed values will be excluded from the primary analysis, and to ensure robustness, values between 0 and 9 will be randomly imputed using a uniform distribution. The nine states with suppressed data are Alaska, Hawaii, Idaho, Montana, Nebraska, North Dakota, South Dakota, Vermont, and Wyoming.

Table 1 displays the average monthly overdose deaths before and after various time points in the sample, indicating an increase in drug overdose deaths in several states, including Oregon, after lockdowns and the implementation of Measure 110, compared to previous years. Figure 1 illustrates the monthly count of drug overdose deaths in Oregon, contrasting it with the average count in the rest of the sample, revealing a similar overall trend. In this sample, California has the highest number of overdose deaths, with a total of 38,208 deaths recorded over the 58-month period. The month with the highest number of overdose deaths across all 50 states and D.C. is April 2021, with 8,713 deaths. Finally, the state-month pair with the most deaths is California in August 2021, recording 964 deaths.

4.2 Additional Predictor Variables

The SCM is sensitive to the choice of matching variables. Predictor variables should be relevant to the outcome of interest, by unaffected by the intervention, and have pre-treatment values available as matching is done on pre-treatment data. For this study, I gather fourteen additional variables to use as matching variables. From the 2019 American Community Survey

(ACS), I aggregate state-level statistics including the portion of people aged 15-24, the portion of people with grade 12 education or higher, the portion of people not living in metro or mixed-metro areas, the portion of people with any health insurance coverage, and the average personal wage income. The CDC's Behavioral Risk Factor Surveillance System (BRFSS) provides information on alcohol and tobacco consumption, and I collect Year 2020 BRFSS state level percentages for the amount of people who have not met the criteria for heavy drinking, defined as adult men having more than 14 drinks per week and adult women having more than 7 drinks per week, as well as percentages of the amount of people who currently smoke tobacco. The BLS provides annual averages of unemployment rates for all US states and DC, and 2020 values are collected. The BEA maintains databases with information at the state level for annual GDP as well as per capita personal income, and 2020 values of nominal annual GDP for each state as well as values for real per capita personal income, in 2012 dollars, are collected.

Finally, dummy variables indicating the existence of five different policies in each state are constructed using data from the Prescription Drug Abuse Policy System (PDAPS). 1 January of 2021 was used as the data of analysis for these policies as this is the last pre-intervention month. The specific policies are whether or not the state provides immunity from civil liability to prescribers for prescribing, dispensing, or distributing naloxone to a layperson, whether or not the state provides immunity from criminal prosecution to dispensers for prescribing, dispensing, or distributing naloxone to a layperson, whether or not the state has a drug overdose good Samaritan law, whether or not the state has syringe service providers operating within it, and whether or not the state considers substance use disorder as sufficient reasoning for involuntary commitment. Table 2 displays a comparison of Oregon's values to an average of the donor pool state's values.

5. Results

5.1 Results

Figure 2 displays the pre- and post-treatment trends in drug overdose deaths in Oregon and the synthetic control. The solid line plots Oregon's actual values while the dashed line plots the values of Synthetic Oregon. This main model uses all mentioned predictor variables as matching

variables, including the average value of monthly overdose deaths during the pre-treatment time period. The synthetic Oregon closely approximates the actual Oregon's pre-treatment trends in overdose deaths. However, after Measure 110 was implemented, the trends in overdose deaths for the actual Oregon and synthetic control began to diverge. This divergence indicates the estimated treatment effect of Measure 110. Figure 3 depicts the gap between Oregon and the estimated counterfactual. Table 3 presents the optimally chosen weights for each donor state. Illinois, Maine Maryland, Nevada, New Hampshire, New Mexico, and Rhode Island receive positive weight in the construction of the main synthetic control.

5.2 Inference

To assess the statistical significance and robustness of the results, I conduct both in-space and in-time placebo studies. The in-space placebo studies involve reassigning the treatment to different states and examining the distribution of treatment effects. The in-time placebo studies involve reassessing the treatment's timing, assigning it to a month before the actual implementation of Measure 110. Table 4 presents the estimated monthly treatment effects and their corresponding p-values, from running general in-space placebo test.

In the 20 months from March 2021 to October 2022, each gap appears statistically significant; moreover, in those 20 months the synthetic Oregon experienced 528 less unintentional drug overdose deaths than the observed Oregon. In those 20 months, the data shows that Oregon experienced 1852 overdose deaths compared to the synthetic Oregon’s 1324, implying that Measure 110 increased drug overdose deaths in Oregon by 40% in the time period of March 2021 to October 2022.

The results of the in-space placebo studies indicate that the probability of obtaining a post/pre-Measure 110 MSPE ratio as large as Oregon's is 0.02439, suggesting the observed treatment effect is unlikely to be purely coincidental; specifically, the monthly estimated treatment values are statistically significant for every post-intervention month in the sample except for February 2021, the first treated month. Excluding the first month of implementation, the results indicate that a total of 528 statistically significant extra overdose deaths occurred in Oregon—or about 26 extra deaths per month.

5.3 Robustness Checks

I perform leave-one-out robustness checks, checking to see if any one donor is having an outsized impact on the construction of the synthetic control. Dropping each of the positively weighted states one at a time, I find no impact to the result. This suggests that no individual state is responsible for the synthetic, building the credibility of the result. Additionally, I note that performing bias-correction synthetic control does not change the results nor does imputing random values for the suppressed data and running the analysis on that data. Performing matching variable sensitivity analysis reveals that my data cannot construct a good synthetic match without using the level of drug overdose deaths itself as a matching variable. Moreover, the BRFSS data on alcohol and tobacco consumption provides relevant information contributing to a better pre-trend match. The demographic and medical coverage variables from the ACS also aid in the construction of the synthetic control but to a lesser extent. The policy dummies do not appear to contribute much helpful information to the estimation. Checking the robustness against many different predictor variable specifications reveals strong robustness to matching variables, except for to the omission of outcome variable itself in the list of matching variables.

In addition to the leave-one-out robustness checks and bias correction, I conduct two in-time placebo tests, using the month of Measure 110's passage in November 2020 following Spencer (2022) and a test using the month of the first stay-at-home order issued in Oregon in March 2020. Figure 4 shows the differing trends when conducting an in-time placebo test using March 2020 as the treatment date, suggesting that the COVID-19 pandemic and its associated stay-at-home order did not cause the observed increase in overdose deaths after Measure 110. Figure 5 shows the results from the in-time placebo test using November 2020 as the treatment period, the month that Measure 110 was passed by Oregon voters. The result shows some weak evidence of an anticipatory impact as the spike in overdose deaths in Oregon in January 2021 is significant. Overall, the robustness checks do not seriously discredit the main results.

6. Conclusion and Discussion

6.1 Conclusion

This study aimed to investigate the impact of Measure 110 on overdose deaths in Oregon. Using a synthetic control approach, I found that there was a significant increase in overdose deaths

following the implementation of Measure 110. My findings revealed a statistically significant estimated treatment effect of 528 additional overdose deaths in the 20 months from March 2021

Several robustness checks show strong support for the result. As my analysis studies drug overdose deaths at the state-level, the results could conceal county- or city-level heterogeneity in the response to Measure 110 in Oregon.

This analysis has many inherent limitations. While the method offers a valuable means of estimating causal effects, it depends on the accuracy of the control group and is very sensitive to the choice of predictive variables. Notably, supply-side factors that may potentially conflate, such as fentanyl availability, have not been incorporated in this study. All potential outcomes methods rely on the assumption that the trend would have been consistent with the control in the absence of treatment. Furthermore, my analysis focused on the first 21 months of Measure 110 and may not capture the longer-term consequences of the program. Other factors—such as the COVID-19 pandemic and associated lockdowns or economic changes—may have contributed to the observed increase in overdose deaths. It should also be emphasized that Measure 110 may have other important outcomes such as arrests and incarcerations that have not been studied in this paper. This study has only investigated Measure 110's impacts on overdose deaths, which does not address the large component of Measure 110 focused on criminal reform, judicial cost savings, and changes to stigma around getting treatment.

6.2 Discussion

The mechanisms underlying the increase in overdose deaths can be speculated at. The impact may be a short-term initial boost of overdose deaths associated with the change of drug policy, without a lasting increase, as has been seen in some cases of cannabis decriminalization (Williams and Bretteville-Jensen, 2014). My results are consistent with Spencer (2022), finding an increase in drug overdose deaths after Measure 110, but inconsistent with Félix et al. (2017) who found a decrease in overdose deaths after Portugal decriminalized drugs. The cause of this discrepancy between Measure 110 and Portugal can only be speculated at, with the shorter time period of analysis on Measure 110 potentially contributing, as well as the fact that Portugal's decriminalization included a more immediate and direct investment in a health-services approach to drug addiction. Oregon has been slow to rollout the treatment side of Measure 110, and might be able to reverse the trend in overdose deaths with sufficient treatment.

This study adds to the discourse on drug policy reform, particularly the potential overdose implications of decriminalizing drug possession. The result indicates a need for adopting a holistic and multifaceted approach to drug policy that incorporates not only decriminalization, but also emphasizes improved access to treatment, implementation of harm reduction strategies, and the development of preventive measures. I recommend that future research continues to assess the long-term repercussions of Measure 110, while delving into the optimal integration of treatment and harm-reduction services with decriminalization to address the complex issue of drug addiction and the prevalence of overdose deaths.

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Tables

Table 1. Mean Monthly Unintentional Overdose Deaths

Oregon, Pre-Measure 110	46
Oregon, Post-Measure 110	91
Rest of Sample, Pre-Measure 110	125
Rest of Sample, Post-Measure 110	170
Oregon, Pre-COVID-19 Lockdowns	39
Oregon, Post-COVID-19 Lockdowns	81
Rest of Sample, Pre-COVID-19 Lockdowns	113
Rest of Sample, Post-COVID-19 Lockdowns	164
Oregon, Pre-Measure 110 Vote	44
Oregon, Post-Measure 110 Vote	89
Rest of Sample, Pre-Measure 110 Vote	123
Rest of Sample, Post-Measure 110 Vote	167

Pre-Measure 110 refers to January 2018 through January 2021, Post-Measure 110 refers to February 2021 through October 2022. Pre-COVID-19 Lockdowns refers to January 2018 through February 2020. Post-COVID-19 Lockdowns refers to March 2020 through October 2022. Pre-Measure 110 Vote refers to January 2018 through October 2020, and Post-Measure 110 Vote refers to November 2020 through October 2022.

Table 2. Summary Statistics of Matching Variables

Variable	*Oregon*	*Donor States (Mean)*
Unemployment Rate	7.6%	7.37%
Is substance use disorder grounds for involuntary commitment under state law?	0	0.70
Do prescribers have immunity from civil liability for prescribing, dispensing or distributing naloxone to a layperson?	0	0.86
Do dispensers have immunity from criminal prosecution for prescribing, dispensing or distributing naloxone to a layperson?	0	0.80
Does the jurisdiction have a drug overdose Good Samaritan Law?	1	0.94
Are SSPs operating in the jurisdiction?	1	0.86
Per Capita Personal Income	56962	58153
Gross Domestic Product	215744	362285
Heavy Drinking Status	7.9%	6.852%
Smoker Status	13.4%	15.4%
Wage Income	206344	221821
Proportion Age 15-24	12.2%	13.1%
Proportion 12+ Years Education	73.77%	71.49%
Portion Rural	11.3%	14.5%
Portion With Any Health Insurance	92.7%	91.4%

Table 3. Chosen Weights

State	*Weight*
Alabama	—
Arizona	—
Arkansas	—
California	—
Colorado	—
Connecticut	—
Delaware	—
District of Columbia	—
Florida	—
Georgia	—
Illinois	0.037
Indiana	—
Iowa	—
Kansas	—
Kentucky	—
Louisiana	—
Maine	0.196
Maryland	0.303
Massachusetts	—
Michigan	—
Minnesota	—
Mississippi	—
Missouri	—
Nevada	0.062
New Hampshire	0.06
New Jersey	—
New Mexico	0.003
New York	—
North Carolina	—
Ohio	—
Oklahoma	—
Pennsylvania	—
Rhode Island	0.34
South Carolina	—
Tennessee	—
Texas	—
Utah	—
Virginia	—
West Virginia	—
Wisconsin	—

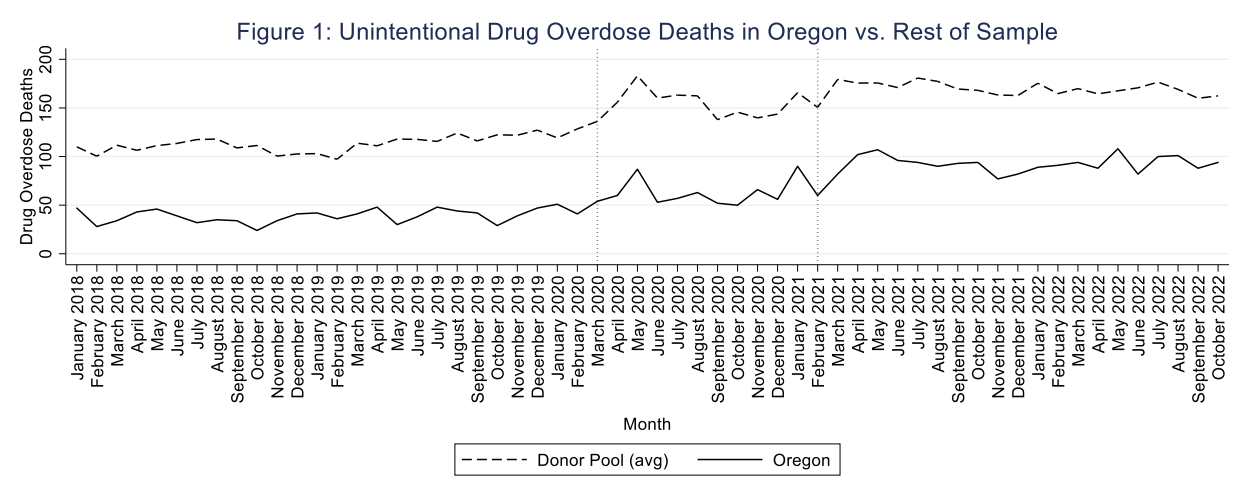
The weights represent the importance of each state in constructing the synthetic control for Oregon. The weights are determined by the Synthetic Control Method and sum to 1. The states included in this table constitute the donor pool, i.e., the set of states that are used to construct the synthetic control. The selection of these states is based on their similarity to Oregon in terms of pre-treatment characteristics.

Table 4. Estimated Monthly Treatment Effects and P-Values

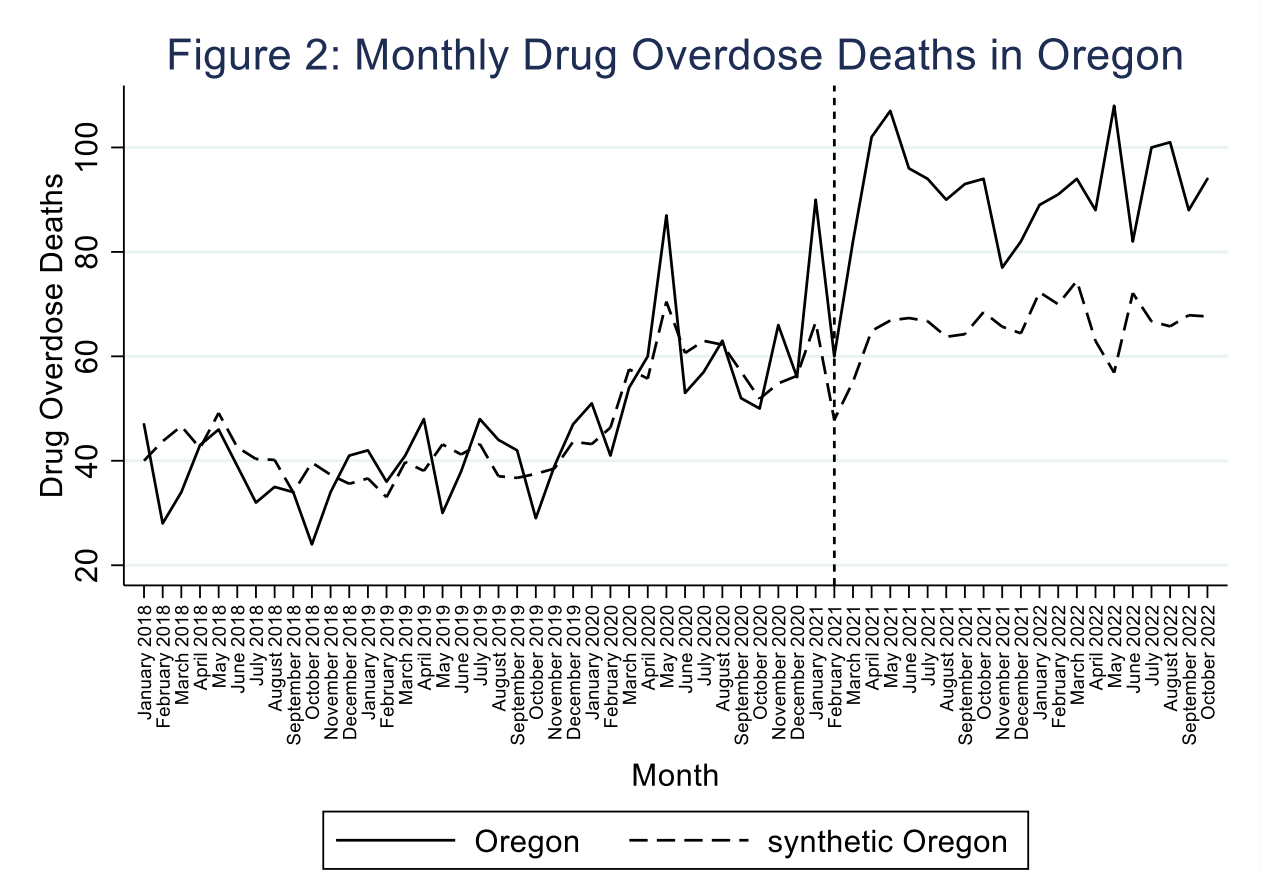
Month	*Estimated Treatment Effect*	*P-Value*
February 2021	12.165	0.2682927
March 2021	26.87	0.0487805
April 2021	37.124	0.0243902
May 2021	40.141	0.0243902
June 2021	28.655	0.0243902
July 2021	27.258	0.0243902
August 2021	26.243	0.0243902
September 2021	28.755	0.0243902
October 2021	25.534	0.0243902
November 2021	11.323	0.0243902
December 2021	17.588	0.0243902
January 2022	16.714	0.0243902
February 2022	21.025	0.0243902
March 2022	19.532	0.0243902
April 2022	25.05	0.0243902
May 2022	51.128	0.0243902
June 2022	9.883	0.0243902
July 2022	33.302	0.0243902
August 2022	35.252	0.0243902
September 2022	20.115	0.0243902
October 2022	26.355	0.0243902

Note that the p-values are calculated through running in-space placebo tests. While the impact for February 2021 is not statistically significantly, the second month is months April 2021 through October 2022 have a MSPE rank of 1. Given that our sample contains 49 states and DC for a total of 50 units, the probability of obtaining a post/pre-Measure 110 MSPE ratio as large as the ratio found for Oregon is 1/50 = 0.02.

Figures



A reminder that here, donor pool refers to all US States except WA and OR, plus DC.



Note this is the main model with all included variables as predictors, and these states having positive weights: Illinois, Maine Maryland, Nevada, New Hampshire, New Mexico, and Rhode Island.

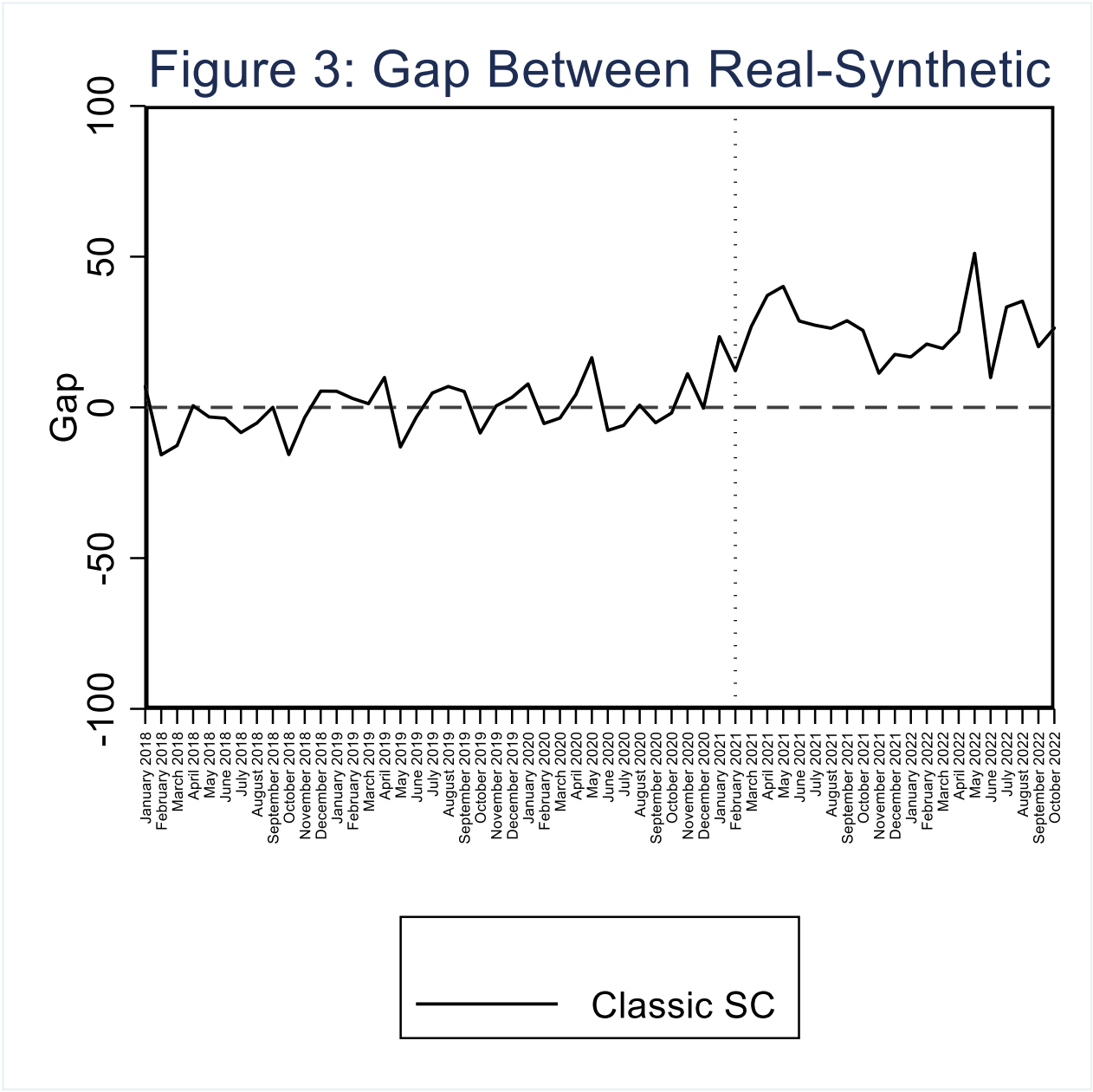


Figure 3: Gap Between Real-Synthetic
Gap
100
50
0
-50
-100
January 2018
February 2018
March 2018
April 2018
May 2018
June 2018
July 2018
August 2018
September 2018
October 2018
November 2018
December 2018
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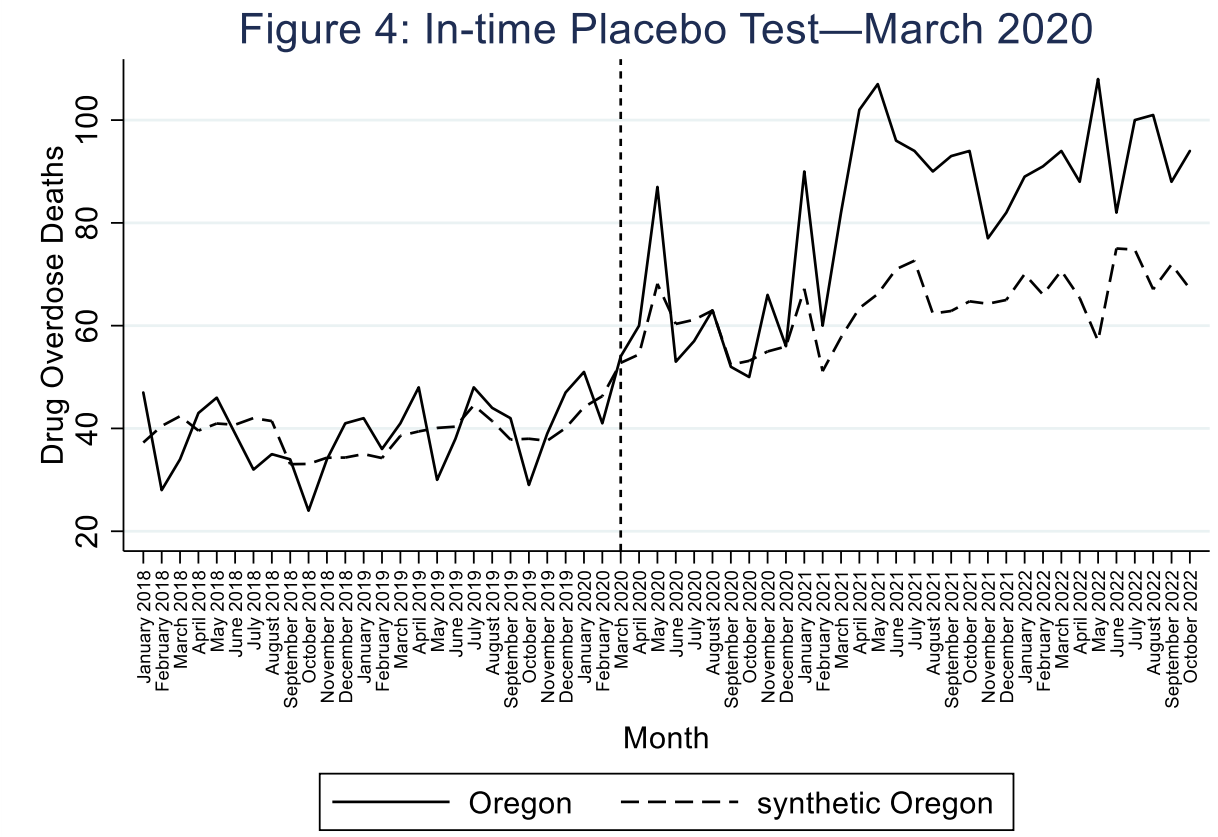
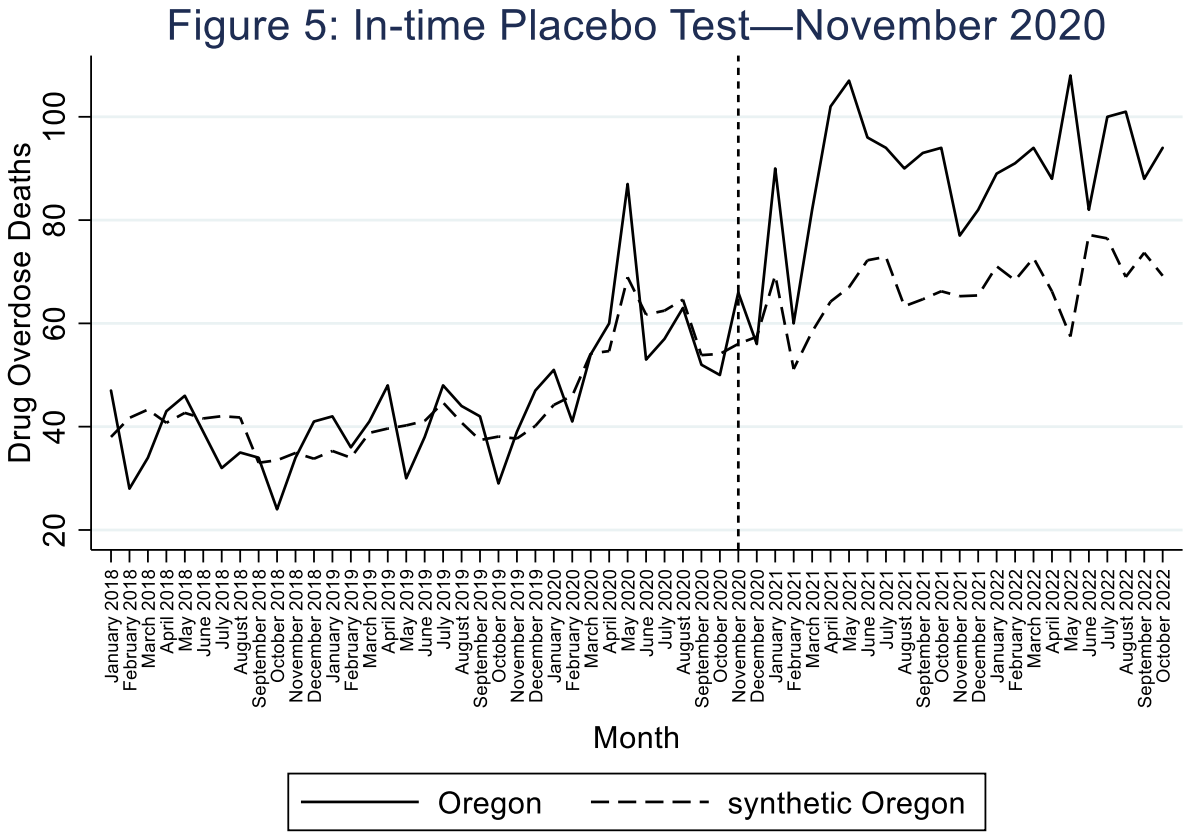


Governor Kate Brown initiated a stay-at-home order in Oregon on 23 March 2020. Similar measures in San Francisco may have been associated with an increase in overdose deaths (Appa et al., 2021).



Measure 110 was passed on 3 November 2020 during the general election. This could lead to anticipatory impacts which have been investigated through backdating the treatment period to November 2020, doing so reveals some evidence of an anticipatory impact as January 2021 had many more Overdose deaths in Oregon than synthetic Oregon.