THE SHORT RUN EFFECTS OF RECREATIONAL MARIJUANA LAWS ON CRIME RATES IN THE U.S: A MULTIPLE DID APPROACH ANALYSIS

A Thesis By

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Abstract:
I use crime rate data for every state in the U.S from 1999 to 2019 from the FBI's Uniform Crime Rate report to study the effects of recreational marijuana laws (RMLs) on different crime categories. To do this, I run three Difference-in-Difference models. The first is for state totals and metropolitan/non-metropolitan area comparisons, and the other two are Group Average Treatment Effects each for average group effects of the different roll out years and the other for the effect by length of exposure to the roll out year. As a country, the results show no effect on violent crime except for decreases in murder cases but there are increases in overall property crime. In specific state comparisons, the effects of RMLs on violent crimes can be mixed but property crimes still increase.

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CHAPTER 1

INTRODUCTION

Marijuana, the dried leaves, and stems of the Cannabis plant, had been strictly illegal in the United States and categorized as a hard drug for many years until recent legislation was passed in Colorado and Washington state in 2012 that allowed for the recreational use of marijuana (Holstege et al., 2014). When consumed, either through smoke or food/drink, its psychoactive effects can give individuals a relaxing or mentally active high. It is physically impossible to overdose on marijuana; one would have to smoke about 2,000 joints in a single day Consuming alcohol heavily in one night, on the other hand, could lead to alcohol poisoning and possible death (Holstege et al., 2014). Indigenous people had used marijuana's effects for psychiatric and painkiller treatment before modern scientists discovered its medical capabilities (Marion & Hill, 2016). After many years of research on marijuana, there is still much we do not know about its effects. From what we do know, it is less dangerous than consuming alcohol, so many pundits argue about whether it should still be considered a class one drug or, as we have seen in recent years, be recreationally legalized

Yet with these differences in medical benefits and non-dangerous recreational use, marijuana has been illegal in the United States and in most parts of the world up until recent legalization of recreational marijuana. For years, thousands of Americans have been incarcerated for marijuana possession and consumption despite the fact that the substance is not very harmful to a person's health (Lee, 2013). This was one of the many arguments' activists used when pushing for the legalization of marijuana in the last decade. Recreational Marijuana Laws (RMLs) were a hot topic in 2012 when the states of Colorado and Washington began adding the legislation referendum in 2014, they became the first states to begin legal sales of cannabis products (Marion & Hill, 2016). Beyond health effects, another push for the legalization of these laws was the belief that crime rates would go down (Marion & Hill, 2016). Now with the roll out of some RMLs in other states, economists like myself are curious to see if these laws have had an impact on crime rates since anyone aged 21 or older can purchase legal cannabis products in most states.

Previous literature was able to study the effects of medical marijuana laws as those were enacted in the early 2000s and late 1990s. The authors found no evidence of any effect on violent crimes but did find an increase in property crimes rates and one explanation provided by some of these researchers found an increase in vehicle break ins one mile away from newly opened dispensaries in Colorado (Burkhardt & Goemans, 2019). I study the effect on crime rates using the same difference-in-difference models that those authors used. Using crime data from the FBI's UCR data set, I collect statistics on violent and property crimes from 1999 to 2019 for all 50 states. The treated states, those that have passed recreational marijuana laws (RMLs), are Colorado, Washington, Nevada, and Oregon. To answer this question, this paper contains different iterations of the difference-in-difference (DID) model: the traditional DID is used for bordering state comparisons of the treated states with their untreated neighbors, and a group time average treatment effects (GTATE) model is used for analyzing the different roll out years of RMLs simultaneously for the treated states against the rest of the country. The GTATE model is reused again to then find the effect by length of exposure, an event study approach, instead of the group effect to analyze if the total effect changes depending on how the roll out years counted. The results from these models reflect some findings in previous literature and will help guide future studies on finding a causal path to analyzing cross border effects of RMLs. Due to some issues with the crime data and parallel trends assumptions, there are some limitations to this paper but in the end I can conclude what previous literature has already identified: when marijuana is legalized, property related crimes are expected to increase and changes in violent crimes are not all explained by legalization.

CHAPTER 2

FINDINGS IN PREVIOUS LITERATURE

This section will quickly summarize the models and results of previous literature that analyzed the effects of marijuana on economic outcomes. There have been a growing number of these types of literature as more states amend RML initiatives and others will soon be seeing them on the next election ballot (Marion & Hill, 2016). For example, the state of New Mexico legalized their own RML in 2021 with legal sales starting in April 2022 (DISA, 2021). For clarity, this section will be split into three brief sections each one discussing supporting econometric models, research on medical marijuana laws (MMLS), and research on recreational marijuana laws.

Econometric Model Support

As discussed in more detail in the methodology section, the model for this study reflects much of previous literature where the author or researcher is looking for a causal path in state effects from a piece of legislature using a Difference-in-Difference model (DID). For example, one study used a DID model on border sharing states to analyze the effects of MML legislation using counties across the U.S and the results showed statistically significant evidence that marijuana becomes a substitute for alcohol (Baggio et al., 2020). Some of the same authors reused this approach in a separate study where they now wanted to analyze the relationship between RMLs and junk food consumption. Still using the same DID approach and controlling for the roll out years of RMLs they find that marijuana and junk food are compliments (Baggio & Chong, 2020).

Another study analyzed the effect of marijuana dispensaries opening in Colorado and their effect on local crime rates. The authors of the study used a DID in for local crime in Denver, Colorado only and found that violent crime cases around dispensaries decreased after RML legalization (Burkhardt & Goemans, 2019). Although this study uses a DID model, it is important to point out that the authors did not have a control group, and this is because the context of their question was to find the effect on crime surrounding dispensary locations, not overall crime in the state. In my study the model contains untreated states as control groups. Similarly, one study analyzed the effect of marijuana decriminalization on crime in the U.S but did not use a DID model. The authors only identify statistically significant changes in the FBI's UCR crime report data for pre and post-marijuana decriminalization years (Maier et al., 2017). This paper did not use a DID model to answer their question, but they used simple descriptive statistic methods to reach their conclusion. From these few pieces of literature, a DID model and observing the crime data before and after marijuana legislation are essential in providing a causal explanation of the effects on crime. Most importantly, because of the nature of the question/study, cross border analysis is also needed in the DID model and this is not only due to it being on marijuana laws. The next study in this review does not analyze the effects of marijuana legalization instead, the authors model the effects of minimum wage across state borders using a DID model. Using contiguous county-pairs sharing a border across the U.S and data on minimum wage policies from 1990 to 2006, the authors find no effects on employment (Dube et al., 2010).

These three pieces of literature do not analyze the effect of marijuana laws on crime but use a DID model because the nature of the question requires a control group being those untreated states or states that do not have the legislation of the variable in question. The remaining literature in this review use DID models and analyze the effects of both MMLs and RMLs.

Findings from Research on MMLs

Using a standard fixed effects model to control for state-specific factors, Shepard and Blackley find no statically significant evidence of a positive effect on both violent and property crime but do find evidence of falling violent crimes after MMLs are rolled out (Shepard & Blackley, 2016). Morris et al. used a two-way fixed effects model and found crime rates were unaffected in states except for Homicides/ Murders which had a decrease in cases or negative effect from MML rollouts (Morris et al., 2014). These two studies used crime data provided by the FBI from their Uniform Crime Report (UCR) where they list statistics on violent and property crimes. Almost all literature studying the effects of marijuana legalization on crime trends uses this data set where other options are found in census tract data. Although the two pieces of literature do not directly use a DID model, it is important to note that one method of running a DID model is by using a two-way fixed effects approach. Just like the literature mentioned as supports to my model, when it comes to studying the effect of a variable in a state with a unique roll out year and there are other states without this variable, the best approach to estimate the closest causal conclusion is by using a DID model.

On the other hand, one study observing crime in the city of Long Beach, California, found evidence that the presence of medical marijuana dispensaries is unrelated to both violent and property crime in local areas, but they are correlated with neighboring areas (Freisthler et al., 2016). Their results find that both main types of crime increase in those adjacent areas to dispensaries but when law enforcement is sent to reduce the number of open dispensaries then the crime decreases in those previously affected areas (Freisthler et al., 2016). Though unlike the literature we have seen and others to come, this paper does not use the traditional DID or two-way fixed effects models. The authors do not use crime data from the FBI’s UCR report and do not apply a control group to their methodology. Instead, they use a Bayesian spatial poison model with census tract data to assess the statistical relationship between dispensaries and crime rates (Freisthler et al., 2016). Another of their studies compares estimates from MMLs to RMLs on crime rates but now at the state level still without using the DID models (Freisthler et al., 2017). In this study, they argue that their model of a Bayesian Poisson spacetime model trumps any other approach because of possible underestimation of true effects and find an increase in marijuana specific crime. They claim a rise in property crime in adjacent areas but not in the immediate surrounding area. As we have reviewed, the previous literature has used cross border DID models to gather the causal effect of a rolled-out variable in a state as it controls for both state and time fixed effects. These authors were funded by the National Institute on Alcohol Abuse and Alcoholism and the National Institute on Drug Abuse, so it seems that not only are their results not causal from the model choice but also have a biased motivation (Freisthler et al., 2016).

Findings from Research on RMLs

The earliest of studies on RMLs was in 2018 by Dragone et al. Using a small time period from the UCR dataset and a DID model, the authors find a reduction in crime rates and a decrease in hard drug and alcohol abuse numbers (Dragone et al., 2018). A similar study found a reduction in violent crime activity and in opioid related deaths, using another DID model and the UCR dataset for crimes (Sabia et al., 2021).

The next significant study to analyze RMLs is one by Zhuang Hao and Benjamin W. Cowan, 2020. The authors compared Colorado and Washington to their bordering states that do not have RMLs using a cross border DID model. Instead of finding the effect on crime, the authors were more interested in finding the spillover effects on the states with no RMLs. Their results find evidence of a significant increase in marijuana use in the neighboring state but mostly among adults, which was initially expected, and found an increase in police enforcement with additional arrests around the state borders. Wu et al. also compares Colorado and Washington to their neighboring states using a DID model as well as using the UCR dataset (Wu et al., 2020). Their results match what you will find in my study where the effects of RMLs on crime are dependent on the type of crime and the state. Yet, the authors still conclude that the overall effect of RMLs on property crime is an increase while violent crimes are not influenced by marijuana legalization.

Revisiting the study mentioned for model support purposes, the authors studied the effects of marijuana dispensary openings on local crime in the city of Denver after recreational consumption of marijuana was legalized in Colorado. They find evidence that violent crimes decrease in above median income neighborhoods after dispensaries open. Other evidence suggests that non-marijuana related crime decreases in areas within half a mile of dispensaries leading the authors to suggest that marijuana and hard drugs are substitutes. There is evidence however of an increase in property crimes up to a mile away from new dispensaries in Denver (Burkhardt & Goemans, 2019). The last relevant study to mention uses a novel identification strategy instead of a DID model but receives similar results to previous studies. They find that the addition of a dispensary in Denver lowers the crime rate in the surrounding area based on crime data from census tracts. The same results of an increase in property crime in exterior neighborhoods surrounding the newly opened dispensary are still found (Brinkman & Mok-Lamme, 2019).

Based on the results found in previous literature and those authors used, I proceed with using a cross border DID model to control for state differences and time fixed effects. This will also benefit the causality path as the model will control for states that did not pass RMLs in the recent decade. The results I find are the same in most cases where violent crimes changes are unexplained by RMLs, but property related crimes increase. For a national analysis, I will use a Group Time Average Treatment Effect model to analyze all treated states in the country together against untreated states and the expected results remain the same although the model changes from previous literature. Before explaining my methodology and data used in more detail, the following discussion goes over the brief history of recreational marijuana laws for the treated states in question.

CHAPTER 3

BRIEF HISTORY OF MARIJUANA LAWS IN THE U.S

In 1914 many states began adopting the prohibition of marijuana without public outcry or legislative debate as most at the time were concerned with the prohibition of alcohol (Siff, 2019). From then on, marijuana soon grew to become a class one drug in the eyes of legislators and most of the public but up until recently, the legality of marijuana has been a recent topic for debate in countries around the world for a few decades (Marion & Hill, 2016). Marijuana has been used for recreational and medicinal purposes in many cultures for a long time now and the increasing public interest in its legalization has sparked the need for further discussion of its potential legality. Opposing pundits argue that its legalization can lead to increases in criminal activity or become a gateway drug. With the growing amount of support for marijuana legalization, future legalization of RMLs in more states is sure to increase in the next decade, so this study will attempt to tackle the former argument and analyze the effects on crime after RMLs are passed in states in the US.

Since beginning this research in late 2020, over 17 states in the U.S have passed legislation to decriminalize marijuana and/or lessen the punishment for possession and use. (Marion & Hill, 2016). There are now also 20 states in the U.S that have passed laws allowing citizens to purchase and use marijuana for medical use (DISA, 2021). For a few years, only four states had passed laws for the recreational use of marijuana (Marion and Hill, 2016) but now as of 2020, that number has grown to seven and some of these are listed in Figure A (DISA, 2021). Like these shifts in different levels of legalization across the country, the history of recreational marijuana laws (RMLs) for each state can differ and at an initial look can be unclear. This section will provide some clarity for this and sum up the RMLs for each state with these laws.

Previous studies have looked at the effect of dispensary openings on local crime after RMLs are passed while too few study the effect of RMLs starting on the year it was passed. As I will explain soon, many of the states did not pass RMLs at the same time, and even when passed the state did not have any recreational sales begin until a year or two after the law was passed. So, the access to marijuana during this grey period of no available commercial sales was only based around growing your own, purchasing medical products, or purchasing it from a nearby state with a legally open dispensary. Because of this, I declare the year that the first commercialized sales of recreational marijuana began to be the year of most importance or in other words the “roll out” year. By using this year, the results of the models will accurately estimate the total effect of marijuana legalization since the effect on society it has is from its usage. What is in question is if its recreational use affects crime rates because that is what comes after it is legalized.

Table 1. RML History

State	Treated	Year RML Passed	*Year Sales Started*	Violent Crime 1999	Violent Crime 2019	Property Crime 1999	Property Crime 2019
California	Yes	2016	2018	627.2	441.2	3177.8	2331.2
Colorado	Yes	2012	2014	340.5	381	3722.9	2590.7
Nevada	Yes	2016	2017	570	493.8	4083.7	2322.1
Oregon	Yes	2014	2015	374.9	284.4	4627.1	2730.6
Washington	Yes	2012	2014	377.3	293.9	4878.3	2681.9
Massachusetts	Yes	2016	2018	551	327.6	2711.5	1179.8
Alaska	Yes	2014	2016	631.5	867.1	3731.7	2910.8
Nebraska	No	Illegal	NA	430.2	300.9	3678.1	2039.3
Kansas	No	Illegal	NA	382.8	410.8	4055.9	2314.5
Wyoming	No	Illegal	NA	232.3	217.4	3222.5	1571.1
Utah	No	Illegal	NA	275.5	235.6	4700.9	2169.3
Idaho	No	Illegal	NA	244.9	223.8	2904.4	1219.5
New Hampshire	No	Illegal	NA	96.5	152.5	2185.4	1209.2
Rhode Island	No	Illegal	NA	286.6	221.1	3295.4	1534.8

Note: Crime values are in cases per 100,000 people

Colorado

RMLs were first passed in Colorado in 2012 and the referendums on that amendment stated that marijuana would be regulated in the same structure as alcohol (Marion & Hill, 2016). This amendment allowed Colorado citizens over the age of 21 to purchase cannabis related products for any use and the freedom to personally grow up to six plants but without being able to use cannabis products in cannabis spaces (Marion & Hill, 2016). Although the RML was passed in 2012, it was not until 2014 that the first dispensary opened in Colorado and recreational sales began (DISA, 2021). In other states the availability and details of RMLs change which I do not control for in my models. Future research should study the differences between RMLs by state to check for additional effects on crime rate. For now, my approaches maintain the assumption that the law differences have no additional influence on crime.

Washington

In Washington, the people began an initiative process to land the RML on the 2012 ballot and by winning over 50% of the votes the law was passed during the 2012 election (Marion & Hill, 2016). It was not until after the law was voted on that the state could then organize regulation procedures for marijuana. Legislators chose to regulate it like alcohol but with some changes to the amount possible to possess. Washington citizens over the age of 21 can purchase up to one ounce of usable marijuana (flower), 16 ounces of marijuana edible products, 72 ounces of it in its liquid form, and only 7 grams of marijuana concentrates (waxes) (Washington State Liquor and Cannabis Board, 2022). Just like in Colorado, although being legalized in 2012, marijuana recreational sales began in early 2014 (DISA, 2021).

Oregon

Moving along in the timeline, Oregon was the next state to successfully pass a recreational marijuana law in 2014 with sales starting in 2015 (DISA, 2021). Like the two previous states, marijuana is regulated just like alcohol, but individuals can only grow up to 6 of their own plants (Weed Seeds USA, 2022).

Nevada

RMLs were passed in 2016 in Nevada with recreational sales first starting in 2017. The only ongoing struggle in its legalization is the specifics of transportation and transportation licenses but cannabis is again regulated like alcohol. Individuals are allowed to grow up to six plants if they live 25 miles away from the nearest dispensary but can only possess one ounce of concentrated marijuana from recreational purchases (DISA, 2021).

Alaska

In Alaska, RMLs were passed in 2014 and, with an executive order from the state governor at the time, recreational sales were able to start in 2016. (DISA, 2021). With the same regulation structure of alcohol, the total amount possible to possess at any moment is only one ounce and it cannot be consumed in public spaces (Davenport, 2021). The only ongoing issues with RMLs in Alaska are decriminalization status as many citizens still have criminal records or are in jail for prior marijuana offenses as the state is working on a way to reverse these past sentences (DISA, 2021). Future research should attempt to observe if decriminalization also affects crime rates in their own way. A reason for this could be easier access to jobs in the market since previous criminal records will now have marijuana related charges wiped. Easier access to jobs could then unemployment and poverty rates leading to reductions in crime cases.

California

California voters approved the 2016 measure to legalize recreational use of marijuana in the 2016 election and recreational sales began in 2018 (DISA, 2021). Its use and possession are regulated like alcohol and similar to Colorado and Washington. California was an early leader in declaring marijuana related businesses essential in the state because of its medical benefits (DISA, 2021).

Massachusetts

Massachusetts voters approved the 2016 ballot measure to legalize recreational marijuana. Citizens could then begin growing and possessing cannabis that same year, but recreational sales did not start until 2018 when the first two dispensaries opened up (DISA, 2021).

CHAPTER 4

DATA COLLECTED

The crime rate data needed for this model is collected from the FBI's Uniform Crime Report (UCR Publications, 2019). This dataset holds crime statistics since 1995 for all 50 states on violent and property related cases with additional specific crime categories for each. I use the entire dataset, from 1999 to 2019. The years 1995 to 1998 are not used because the dataset during these years does not contain a per 100,000 inhabitants' statistic for each state. To remain consistent, I use the per 100,000 inhabitants' rate, provided by the FBI, for all models that analyze the entire state. For the models which will analyze the specific metropolitan and nonmetropolitan areas of Colorado, I use the estimated total number of cases that is provided in the same dataset. Although there is an "area actually recording" statistic, I stick to the FBI's estimated value as it accounts for any crimes possibly not reported (UCR Publications, 2019).

From the data set, I pull all available subcategories from violent, and property related crime: Murder/Manslaughter, Rape, Robbery, Aggravated Assault, Burglary, Larceny Theft, and Motor Vehicle Theft. It is also important to add that there was not one null, NA, or blank value in the dataset; every state had a value for each category from 1999 to 2019. Crime data on Rape cases was the most difficult to assess. In 2011, the FBI had its definition of rape redefined as recommended by the FBI's Criminal Justice Information Service Division Advisory Policy Board, and beginning in 2013 the new reporting definition was implemented (UCR Publications, 2019). This revision assisted crime reporting with being able to identify more accounts of rape than previously accounted for and made the crime rate statistic more accurate to the actual number of cases. So, when combining the overall data for rape for a dataset from 1999 to 2019, there is a slight jump in the number of cases from 2013 to 2014. I could not remain consistent with one or the other because the FBI removed the legacy statistics after 2016. Keeping this in mind, some of the effects on rape cases from RMLs could be a bit biased as the total reporting of rape cases from 1999 to 2019 is not consistent, creating the first limitation of this paper.

Moving forward, once all the data was collected, I gave the states with RMLs a dummy variable, 1, and are now labeled as the treated states (Alaska, California, Colorado, Massachusetts, Nevada, Oregon, and Washington). All states received a unique identifier, and the treated states received a variable indicating the year of when treatment started as mentioned in the Brief History of Marijuana Laws section. For example, since Alaska began recreational sales in 2015 than it receives the value 2015; all the untreated states receive a 0. These steps were necessary to run the Difference in Difference with multiple periods model produced by Callaway and Sant ’Anna, which will be explained in further detail in the Methodology section. A summary of the data can be reviewed in Tables 2 and 3.

Table 2. Violent Crime Descriptive Stats

Descriptive Stats	Overall Violent Crime	Murder	Rape	Robbery	Aggravated Assault
Mean	385.83	4.57	36.53	93.81	250.92
Median	353.10	4.50	34.20	88.05	225.50
Standard Deviation	163.92	2.36	14.78	53.67	120.93
Minimum	66.90	0.50	11.20	6.10	34.10
Maximum	885.00	14.20	161.60	281.60	651.40
Sample Size	1050	1050	1050	1050	1050

Note: Estimated using all crime data for each state from 1999 to 2019. Values are in terms of per 100,000 people

Table 3. Property Crime Descriptive Stats

Descriptive Stats	Overall Property Crime	Burglary	Larceny Theft	Motor Vehicle Theft
Mean	2975.27	616.26	2082.81	276.20
Median	2878.80	575.30	2042.85	246.30
Standard Deviation	849.11	243.30	542.33	156.62
Minimum	1179.80	126.30	911.80	28.40
Maximum	5833.40	1286.90	3963.70	1115.20
Sample Size	1050	1050	1050	1050

Note: Estimated using all crime data for each state from 1999 to 2019. Values are in terms of per 100,000 people

From the summary statistics of total crime in the United States, we can see the average number of violent crime cases in the United States during this time period is around 386 cases and for property crimes is 2975 per 100,000 people. Differences between states on the violent crime rates are not as large as differences in property crimes upon observing the size of the standard deviation. This could be due to the difference in starting crime rate between states in 1999 or 2009 as mentioned in the Brief History of Marijuana Laws section. In most cases, states with RMLs had higher rates of crime in the starting years than states without them, but in some cases, like Colorado and Kansas for example, Kansas' violent crime rates in 1999 and 2009 were 382 and 400 while Colorado's were 340 and 337.8 respectively.

Based on the information in the descriptive statistics that the decreases in crime for treated and untreated states differ from one another, I assume there will be an issue with the parallel trends of crime rates. To begin to test if this is true, I create line graphs to visualize if the parallel trends are met for the total United States; these can be reviewed in Figures 1 and 2.

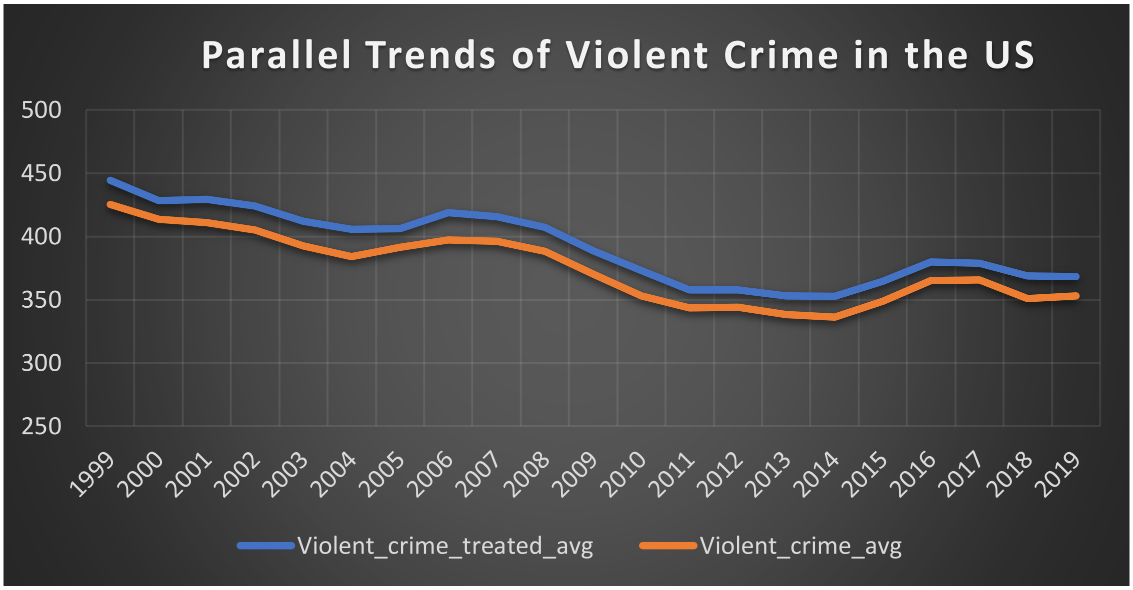

Figure 1. Parallel Trend for Violent Crimes in the US.

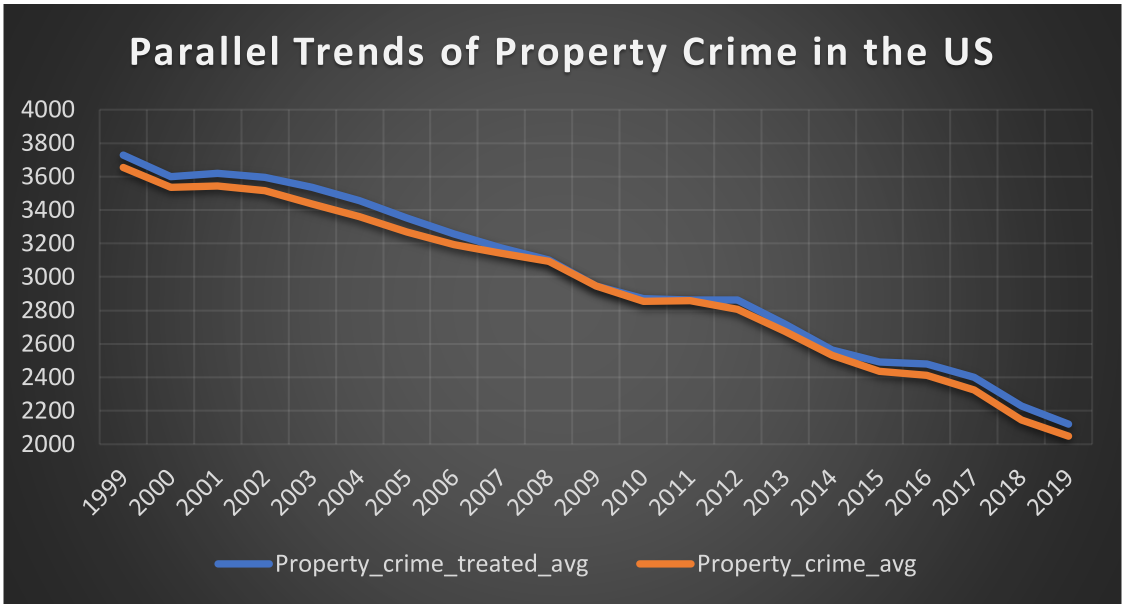

Figure 2. Parallel Trend for Property Crime in the US.

Even though this is only a visual representation of the parallel trends, it is enough to begin considering using a robust data set that avoids the cluster of 2008, 2009, and 2010. This data set is now the main data for my models which will only contain data from the years 2010 to 2019. For robustness checks I will use all available data to identify differences in the results and show why controlling for parallel trends is needed in DID models. To provide one final support of how the parallel trends are not supported in the property crime rates, I conduct a placebo test with the results shown in Table 4.

By only using data from before the treatment period, in this case all years before 2014, and selecting two fake treatment periods, then I can run a Difference-in-Difference model that I was planning to use for the state comparisons and if there is an effect on crime it implies that there is a violation of the parallel trends model (Huntington-Klein, 2022). Unfortunately, we cannot use a placebo test on the main data set as this test functions only by using data before the initial treatment period. From the placebo results above, only property crimes are statistically significantly affected by the fake treatment, so just like the visual representation, the parallel trends assumption is not valid for property crimes.

Table 4. Parallel Trends Test of Historical Crime Rate Data

	Violent Crime T1	Violent Crime T2	Property Crime T1	Property Crime T2
FakeTreat1TRUE	10.38		295.339***	
	(-10.187)		-89.03	
FakeTreat2TRUE		20.07		161.132*
		(-17.264)		(-91.779)
Num.Obs.	750.00	750.00	750.00	750.00
R2	0.94	0.94	0.92	0.91
R2 Adj.	0.93	0.93	0.91	0.91
R2 Within	0.00	0.00	0.02	0.00
AIC	7874.70	7874.10	10445.90	10459.60
BIC	8175.00	8174.40	10746.20	10759.90
Log.Lik.	-3872.37	-3872.05	-5157.95	-5164.82
Std.Errors	by: State	by: State	by: State	by: State
FE: State	X	X	X	X
FE: Year	X	X	X	X

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

There is some evidence in certain cases where parallel trends are not met for violent crimes, and this is seen in the Colorado state comparisons with Kansas and Nebraska; seen in Figure 3. This further supports the need to rerun all my models in this study using the robust data set only including crime data from 2010 to 2019. All results for both versions of each model are discussed in the results section.

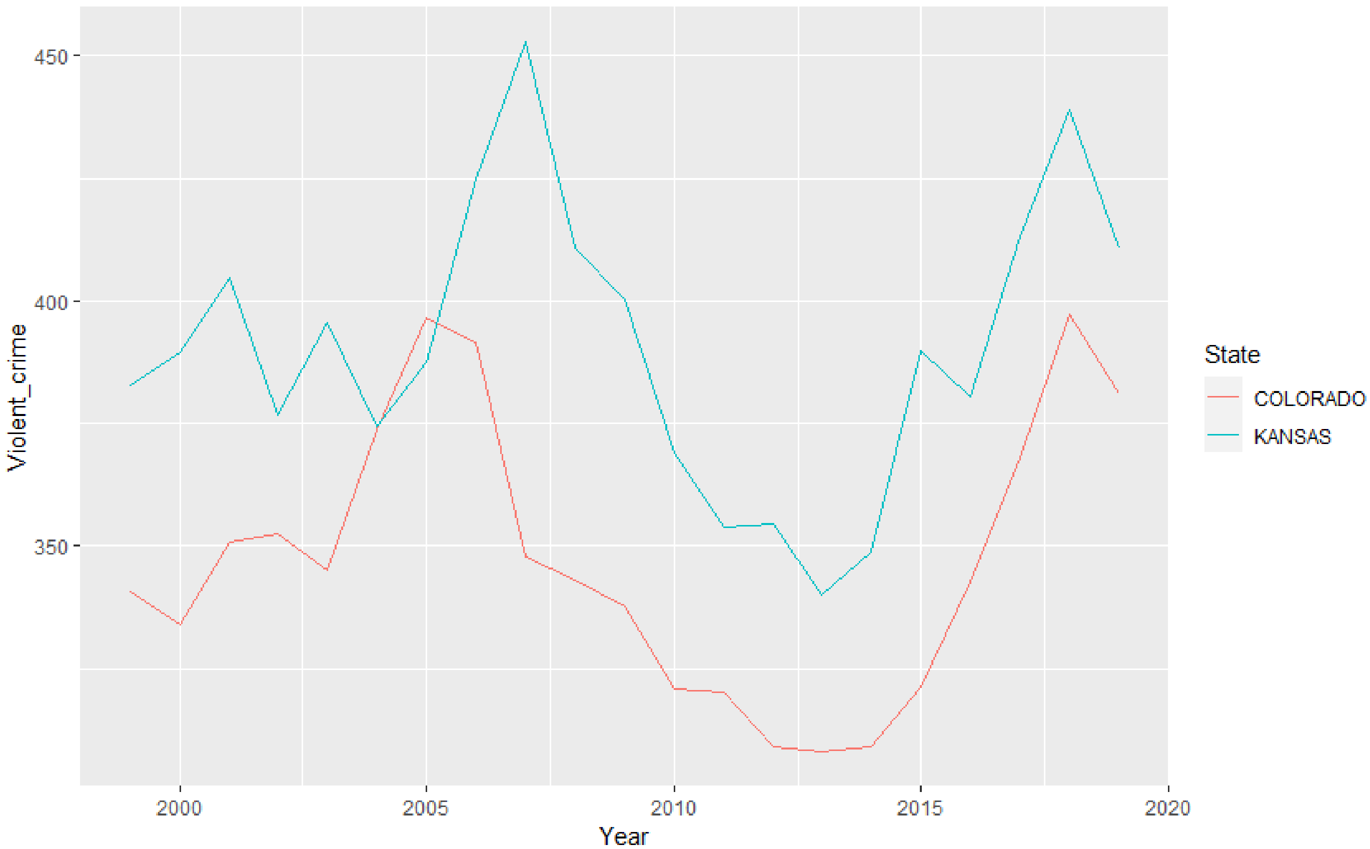

Figure 3. CO vs KA Parallel Trends for Violent Crime.

CHAPTER 5

METHODOLOGY

This study uses three variations of the simple Difference-in-Difference model (DID) which provide evidence of what I believe to be a causal identification of recreational marijuana law effects on crime rates. Because of the nature of my question, the year when recreational sales begin in a state is the event study of the model or in other words the rollout year. In other research, different models analyze these event studies but what separates event study models from a DID is the use of a control group (Huntington-Klein, 2022). As stated earlier, the control groups in my research are states with no RMLs and the treated states are those with RMLs. Since my question is to understand the effects on crime in the U.S from RMLs, then I need to control for the group differences, in other words, the state differences. We also know that time can affect crime rates itself, so by adding in a control group the model can control for time differences between the two groups (Huntington-Klein, 2022). Since we control for group and time differences this way, the results of the DID model will have what is called a counterfactual. A counterfactual is the change in the variable of interest we would expect to see if the treated group never received the treatment (Huntington-Klein, 2022). In a short description, the DID model will show us how much more crime in the treated group than the control group when moving from before RMLs to after and by how many cases would crime rates still be affected by time if RMLs were not passed. The rest of this section will explain each iteration of the DID models used for this study in more detail.

The first is a traditional Difference-in-Difference model, and it is used only for the individual state comparisons for both the state crime totals and Colorado's area-specific crime rate estimates. The DID for the state crime totals will provide an overview of crime trends in the treated states by including the counterfactuals in the tables and finding the effect of RMLs on crime for individual states. The DID equation for both these models, as the only difference between the two is the data used, is:

$$CR_{gt} = \alpha_g + \alpha_t + \beta_1 Treated + \epsilon \tag{1}$$

where CR stands for Crime Rates, α represents the group/state (g) and time (t) fixed effects, and our DID estimator is given by the β1 coefficient value. The variable α_g represents a set of fixed effects for the corresponding group while α_t is a set of time fixed effects for the period the group is in. Treated is a binary/ dummy variable that indicates whether the state/ group is being treated (Huntington-Klein, 2022). This equation/model is applied to the following comparisons: Colorado vs Kansas, Nebraska, Wyoming, and Utah; Washington and Oregon vs Idaho; and Nevada vs Idaho and Utah. The same approach is applied to the Colorado area-specific crime rate estimates.

The reason why these comparisons are so specific is to control for state differences using only states that share a border. Models for the Colorado area-specific crime estimations will also be organized the same way, so the specific comparisons will remain the same and the only difference there will be is the data used. The same type of analysis can be seen in a research paper using DID to compare minimum wage effects between states (Dube et. Al., 2007). Based on that previous literature and the special circumstances of RMLs in the U.S, this border sharing comparison is essential for controlling state/group differences in the traditional DID model. The other iterations of the DID model do not need to control for this as they rely on controlling for different rollout periods.

The next models to be used in my analysis are new iterations of the traditional DID models as two recent econometricians have created a new method of DID for problems where there are more than one rollout period. When I run the models for the state comparisons, there is only one rollout year in that equation, for example, if it were for Colorado, the starting treatment year is 2014 but for Nevada, the starting treatment year is 2017. Brantly and Sant'Anna (2021) develop the Group-Time Average Treatment Effects, which allows for multiple rollout years in an estimate. Instead of a DID estimator, this model will estimate the ATT which is the average effect of participating in the treated group at a certain point in time (Callaway & Sant'Anna, 2021). In this case, the ATT is the average effect RMLs have on crime in the treated state at a certain point in the rollout period. Here is the equation from the original authors with edits made in the variables to represent my question of interest:

$$ATT_{CR}(g,t) = E[CR_t - CR_{g-1}|G = g] - E[CR_t - CR_{g-1}|C = 1] \quad (2)$$

The $ATT_{CR}(g,t)$ variable represents the average effect on crime for a rollout year g and time t. $CR_t - CR_{g-1}|G = g$ is the outcome effect on crime for the treated group with rollout year g. $CR_t - CR_{g-1}|C = 1$ is the outcome effect on crime for the untreated group since C = 1 with g being the same rollout period and t being the same time value (Callaway & Sant'Anna, 2021). At its core, it is still a basic treated minus untreated calculation but due to the many different rollout periods of RMLs this model is the best to use to separate the effect by group and take their average to find the total group average effect on crime in the U.S.

Alternatively, a second iteration of this model estimates the ATT using the average effect by length of exposure to the treatment in question, not by the average effect of each rollout group otherwise known as an event study or dynamic approach. The equation for this model, with variable changes to match my question is as follows:

$$\theta(e) = \sum_{g=t}^{T} 1\{g + e \leq T\} ATT_{CR}(g, g + e) P(G = g|G + e \leq T) \quad (3)$$

From the first iteration of this model, g still represents a rollout year in question and ATT_{CR} is the average effect of participating in the treated group G. Variable e is the total time periods after the rollout year and variable T is the total time periods in the data set/model. $\theta(e)$ is the new statistic that is the average effect of participating in the treatment group for exactly e time periods (Callaway & Sant'Anna, 2021). A regression friendly equation for this model is:

$$ATT_{CR}\big(\theta(e)\big) = E[\theta(e)_t - \theta(e)_{g-1}|G = g] - E[\theta(e)_t - \theta(e)_{g-1}|C = 1] \quad (4)$$

As you will see in the results section, when we run the model using the dynamic approach, we still receive an ATT statistic, but it would be then estimated by taking the average effect of each individual length of exposure effect, $\theta(e)$, for each rollout period group. All these models are applied for special purposes in this paper to get close to a solid conclusion of the causal effect of RMLs on crime rates. For a bird's eye view of the effects on the entire country, I use the Group-Time average Treatment Effect model to see the average effect RMLs have on each type of violent and property crime in the U.S based on the rollout groups. I will then use the dynamic version of the model to estimate the effect by length of exposure to the RML treatment by rollout group and see if this estimation differs from the group effect version. The state comparison models will use the traditional DID estimation controlling for time effects and group differences.

Because of the lack of parallel trends in property crime cases in the nation, I mentioned I my main models will use only data from 2010 to 2019 to control and apply the parallel trends assumption for both violent and property crime to be on the safe side. To further support this decision, I run a robustness check for each model conducted which uses all available crime data from 1999 to 2019. What I find is that the effects in the robustness check do not mirror much of previous literature and the effects in the state comparisons differ greatly where we would expect to see most of the same results for all comparisons of a single state (Colorado has four so we expect the results to be quite similar in the four). The results for robustness check models can be found in Appendix B and some of the specific differences between them and the main models are explained in the corresponding Findings sections.

CHAPTER 6

FINDINGS

Introduction/RoadMap

In this section I will go over the results for the main models which only use crime data from 2010 to 2019. Again, the reason for this (detailed in the Data section) is to control for the parallel trends assumption that is violated for property crimes from 2007 to 2009. There is some difference between these results and the results of models the results of models using all available data, which will be explained in further detail after presenting the main results. First, I will go over the Average Treatment Effect Model results for Group Effects and Dynamic/ Event Study effects. Afterward, I will discuss the changes in the state comparison models for both overall state statistics and area-specific results.

GTAFE Results Using Group/Cohort Aggregation

Starting with the results for the models analyzing the effects at a national level, the ATT values, and their statistical significance match results from previous literature. The ATT statistics, which represents the average effect RMLs have on crime and by each group, for overall violent crime in the nation is statistically insignificant; this is shown in Table 5. So, after RMLs are passed and recreational sales begin, the change in violent crime cases is not explained by recreational marijuana legalization. Although, the ATT statistics for the 2015, 2016, and 2017 groups are statistically significant. This means that for Oregon (2015), Alaska (2016), and Nevada (2017), crime is influenced by recreational marijuana sales and these effects are an increase of 22 cases per 100,000, increase of 106 cases, and a decrease by 139 cases respectfully. The aggregate ATT for effect on total violent crime is estimated by averaging these group effects, so one can say that the change in crime from RMLs for Nevada offsets increases in crime from other states.

Table 5. Summary of ATT's based on group/ cohort aggregation:

Total Violent Crime Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	1.3777		6.5801	-11.5191	14.2744
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	11.637	15.709	-22.2785	45.5526
	2015	22.5544**	6.6606	8.1742	36.9346
	2016	106.3744**	5.1797	95.1915	117.5574
	2017	-139.3488**	4.48	-149.0212	-129.6765
	2018	-1.6052	8.2337	-19.3818	16.1713
Total Property Crime Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	198.0355**		96.695	8.5169	387.5541
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	118.4351	165.36	-261.3849	498.2551
	2015	282.82**	28.517	217.3187	348.3213
	2016	661.8721**	25.63	603.0011	720.743
	2017	108.7062**	18.058	67.2294	150.183
	2018	47.9901	34.591	-31.462	127.4423

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Alternatively, as we see in Table 5, the ATT for overall property crime in the nation is statistically significant and shows an increase of 198 cases per 100,000 people. In other words, the effect on property crimes in the U.S from recreational marijuana is an increase of 6.7% relative to the national mean. For these results, the same three groups are also statistically significant but not with positive effects on crime which helps conclude why there is an increase in overall property crime in the U.S.

Some specific types of crime with ATT's that also show statistically significant results are Murder, Rape, and Larceny (seen in Tables 6 and 7). For murder cases, its ATT statistic reflects a drop in less than one case per 100,000 people in the nation or, in other words, a drop a drop in 5.7% of the national average. Only the 2016 and 2017 groups have statistically significant ATTs and both are negative with the 2017 group having a slightly larger negative effect on crime. So, the effects on crime in Alaska and Nevada from RMLs add the most to the overall effect on crime in the U.S.

Table 6. Summary of ATT's based on group/ cohort aggregation

Murder Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	-0.262**		0.103	-0.464	-0.0601
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	-0.276	0.1949	-0.7375	0.1855
	2015	-0.1605	0.1283	-0.4643	0.1434
	2016	-0.443**	0.1259	-0.7413	-0.1447
	2017	-0.6403**	0.0908	-0.8555	-0.4252
	2018	-0.0192	0.1144	-0.2901	0.2518
Rape Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	4.9666**		1.9698	1.1059	8.8273
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	2.3773	1.7526	-1.797	6.5517
	2015	2.4651**	0.7977	0.5652	4.3651
	2016	17.4791**	0.9364	15.2487	19.7094
	2017	8.8279**	0.8202	6.8742	10.7816
	2018	0.6198	0.6797	-0.9993	2.2388

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the case for rape crimes, the results show an increase of a rounded five cases per 100,000 people or an increase of 13.7% relative to the national average. Here, all three groups for 2015, 2016, and 2017 are statistically significant with positive increases in rape cases. The largest effect of the groups is for Alaska (2016) and ten cases lower is Nevada (2017).

For the last of GTATE results based on group/ cohort aggregation larceny theft's ATT, seen in Table 7, is statistically significant and like previous literature for effects on property crime, it is positive. The ATT shows an increase of a rounded 122 cases per 100,000 people or an increase of 5.9% relative to the national mean. The same three groups are also statistically significant as before but now Alaska has the highest effect on the national ATT.

Table 7. Summary of ATT's based on group/cohort aggregation

Burglary Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	46.1747		26.767	-6.288	98.6373
Group Effects:	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	15.0271	55.314	-147.4229	177.4771
	2015	77.7972**	9.6519	49.4507	106.1438
	2016	136.5942**	5.1003	121.6153	151.5731
	2017	30.8295**	5.5328	14.5802	47.0787
	2018	23.9738**	6.8492	3.8586	44.0891
Larceny Theft Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	121.9102**		45.269	33.1838	210.6366
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	78.2467	85.219	-97.7763	254.2697
	2015	115.5498**	18.444	77.4525	153.647
	2016	349.9913**	24.572	299.238	400.7446
	2017	130.1612**	12.83	103.6595	156.6629
	2018	50.5878	32.633	-16.8164	117.992
Motor Vehicle Theft Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	29.949		25.962	-20.9364	80.8344
Group Effects:	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	25.1886	45.079	-75.7444	126.1216
	2015	89.353**	6.4683	74.8702	103.8359
	2016	175.2145**	4.0141	166.2268	184.2023
	2017	-52.1868**	3.4941	-60.0103	-44.3633
	2018	-26.5576	13.712	-57.2586	4.1435

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Based on these tables, disregarding the effect on rape cases as it could be potentially skewed because of the change in the dataset counts, the effects are reflective of previous literature as we see increases in property crime, especially larceny theft, which is the most abundant type of property crime in the nation. We also see either no effect on violent crime or a decrease as shown in the model for murder cases with a negative ATT.

GTAFE Dynamic/Event Study Results

This section covers the results for the GTATE models estimated by using dynamic approach otherwise known as the effect by length of exposure. In these models, the ATT statistic still reflects the effect on crime, not the effect for that rollout group year, but the effect on crime for how many years exposed to RMLs the treated states were/are. For these new results, only two types of crime are statistically significant unlike the results for the group effect models.

In Table 8, we see the only statistically significant results for changes in crime based on length of exposure to recreational marijuana sales in the nation and those are for only Murder and Rape. The ATT values for both crimes however do not change so there would still be a decrease in Murder cases and an increase in rape cases experienced at a national level. It is still important to point out that the effect on rape cases is possible to not be causal due to the change in data reporting. Although the results are similar to the group effect models, there is one key difference in the statistical significance of the results for murder cases. The ATT statistic for event time 2 is statistically significant at the 95% confidence level too. This represents a decrease in murder cases of one per 100,000 people in the nation after being exposed to recreational marijuana sales after two years. Compared to the national average, this is a drop in 5% of murder cases in the U.S after two years of RML legislation. Other results, which are shown in the appendix, do have some statistical significance in certain event times, but because their overall ATT is statistically significant then there is no effect on that crime at a national level.

Table 8. Summary of ATT's based on event-study/dynamic aggregation:

Murder Cases	ATT		Std. Error	[95% Conf. Int]	
	-0.2812**		0.1189	-0.5143	-0.0481
Dynamic Effects	Event time	Estimate	Std. Error	[95% Simult. Conf. Band]	
	-7	-0.3616**	0.1546	-0.7098	-0.0134
	-6	-0.5837	0.3155	-1.2942	0.1267
	-5	-0.2285	0.2354	-0.7585	0.3015
	-4	0.1902	0.4128	-0.7392	1.1196
	-3	0.1276	0.1566	-0.225	0.4802
	-2	0.101	0.2001	-0.3495	0.5514
	-1	0.4578	0.3173	-0.2567	1.1723
	0	-0.0223	0.3212	-0.7455	0.701
	1	-0.2063	0.118	-0.4719	0.0593
	2	-1.1763**	0.4814	-2.2603	-0.0922
	3	0.0436	0.4333	-0.9321	1.0193
	4	0.0752	0.207	-0.391	0.5414
	5	-0.4012	0.1967	-0.844	0.0417
Rape Cases	ATT		Std. Error	[95% Conf. Int]	
	5.0549**		2.4834	0.1875	9.9223
Dynamic Effects	Event time	Estimate	Std. Error	[95% Simult. Conf. Band]	
	-7	-1.957**	0.4649	-2.9161	-0.9979
	-6	-0.7915	0.7389	-2.3159	0.7329
	-5	-2.9762	4.9254	-13.1376	7.1852
	-4	5.013	4.9891	-5.2798	15.3058
	-3	3.4801	7.3469	-11.6769	18.637
	-2	-1.0336	4.2907	-9.8855	7.8184
	-1	0.8472	2.9457	-5.23	6.9243
	0	3.9233	3.1704	-2.6173	10.4639
	1	0.8053	3.459	-6.3308	7.9414
	2	11.3009	7.4766	-4.1237	26.7256
	3	8.9215	5.2311	-1.8705	19.7135
	4	3.6853	3.3156	-3.155	10.5255
	5	1.693	2.181	-2.8066	6.1926

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Colorado and Kansas Comparison

Before diving into the results for each comparison, I will briefly explain the counterfactual scenario for each which is what would crime have looked like if RMLs were not passed in the treated state. Based on the results for Table 9, Colorado would have had lower property and overall violent crime if RMLs were not passed compared to Kansas. Results for this model show statistical significance in the DID estimators for only overall property crime, larceny theft, and motor vehicle theft cases. There is no statistically significant evidence that violent crime is affected in Colorado by RMLs. This mirrors previous literature as only property crimes are positively affected, and violent crimes are not explained by RMLs.

Table 9. CO vs KA, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	3072.500***	646.300***	2199.350***	226.875***
	-56.766	-24.427	-35.694	-18.253
treated	-414.075***	-145.325***	-269.550***	0.75
	-80.28	-34.544	-50.479	-25.813
time	-422.483***	-176.600***	-269.700***	23.775
	-73.285	-31.535	-46.08	-23.564
didCOKA	410.092***	80.608*	241.567***	88.000**
	-103.641	-44.597	-65.168	-33.325
Num.Obs.	20	20	20	20
R2	0.734	0.79	0.757	0.682
R2Adj.	0.684	0.751	0.712	0.622

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

From the statistically significant DID estimators, I can conclude Colorado had an increase of 410 overall property crime cases, 241 for larceny theft, and 88 for motor vehicle thefts, in terms of 100,000 people in the state, due to the passing of RMLs. These conclusions hold true for this comparison between Colorado and Kansas only as we will see with the next model certain effects RMLs have on crime rates depend on the states being compared.

Colorado and Nebraska Comparison

In the robustness check for this state comparison, there is no statistically significant evidence that RMLs influence any type of crime in Colorado and the counterfactuals suggest that only rape cases would still have increased over time even if RMLs were not in the picture; all other types of crime would have decreased. When I ran the main model, the results came out much different as seen in Tables 10 and 11.

Table 10. CO vs NE, 2010 to 2019 Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	263.550***	3.150***	38.925***	56.700***	164.800***
	-10.658	-0.203	-3.319	-2.312	-8.335
treated	50.925***	-0.2	7.225	6.325*	37.500***
	-15.073	-0.288	-4.694	-3.27	-11.787
time	26.100*	-0.550*	16.842***	-8.717**	18.45
	-13.76	-0.263	-4.285	-2.985	-10.76
didCONE	12.592	1.117***	1.692	9.025**	0.867
	-19.46	-0.371	-6.06	-4.222	-15.217
Num.Obs.	20	20	20	20	20
R2	0.754	0.496	0.723	0.718	0.668
R2Adj.	0.708	0.401	0.672	0.665	0.606

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

For violent crimes only murder and robbery cases have statistically significant DID estimators and both increase being the opposite of previous literature and not seen in the previous comparison. So, Colorado's murder and robbery cases increase by 1 and 9 cases per 100,000 people respectively compared to Nebraska. The results for property crime, however, do match that of past findings. In Table 11, overall property crime, larceny theft, and motor vehicle theft are shown to have statistically significant DID estimators reflecting a positive effect on those cases. If Colorado had not passed any RML, then their crime rate relative to Nebraska would have increased for violent crime and property crime would have actually decreased.

Table 11. CO vs NE, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	2701.100***	468.975***	2011.400***	220.750***
	-55.002	-20.512	-38.34	-18.869
treated	-42.675	32	-81.6	6.875
	-77.785	-29.008	-54.221	-26.686
time	-464.250***	-143.408***	-346.283***	25.4
	-71.008	-26.481	-49.496	-24.36
didCONE	451.858***	47.417	318.150***	86.375**
	-100.42	-37.45	-69.998	-34.451
Num.Obs.	20	20	20	20
R2	0.801	0.769	0.788	0.682
R2Adj.	0.764	0.726	0.748	0.622

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Colorado and Utah Comparison

The results that show some statistical significance for this model are shown in Table 28 in Appendix A and are not shown here because they are not significant at the 95% confidence level. There is no statistically significant evidence that RMLs affect any type of crime in Colorado when compared to Utah. The counterfactual in this case however does show an increase in violent crime with a decrease in property crime in Colorado. Interestingly enough the robustness check of this model that uses all available crime data since 1999 shows the same result of no significant DID estimators.

Colorado and Wyoming Comparison

This final model of the Colorado state comparisons reflects similar results as the one with Kansas. The results found in Table 12 show statistically significant increases in crime for overall property crime, larceny theft, and motor vehicle theft.

These results reflect that of previous literature's findings as only property crimes are affected by RMLs. Listing the three respectively, the increases would total 457 cases, 391 cases, and 87 cases per 100,000 people in Colorado. Since these results are not shown in the robustness checks results and reflect findings from previous literature, then it is safe to conclude that using the robust data set for the Colorado state comparisons provides a more accurate conclusion for the effects of RMLs. Differences in the Colorado and Utah model could stem from area-specific influences from metropolitan and non-metropolitan areas which are explained in the third part of the results section. But before skipping ahead, the other state comparison model results with Nevada, Washington, and Oregon, do not reflect all the same results as the Colorado comparisons.

Table 12. CO vs WY, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	2305.050***	353.350***	1852.425***	99.275***
	-52.93	-13.852	-43.212	-18.363
treated	353.375***	147.625***	77.375	128.350***
	-74.855	-19.59	-61.11	-25.969
time	-469.850***	-74.617***	-419.908***	24.675
	-68.333	-17.883	-55.786	-23.706
didCONE	457.458***	-21.375	391.775***	87.100**
	-96.637	-25.291	-78.893	-33.526
Num.Obs.	20	20	20	20
R2	0.933	0.911	0.884	0.9
R2Adj.	0.921	0.895	0.863	0.881

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Nevada and Utah Comparison

The results for Nevada’s comparison mirror that of previous literature with seeing increases in property crime but most importantly in the types of crime most abundant for both violent and property related cases. In Tables 13 and 14, we see the results for the comparisons model of Nevada and Utah; unlike the Colorado model, there are significant results for two types of crime.

For violent crimes, only aggravated assault has a statistically significant DID estimator reflecting a decrease in 57 cases per 100,000 people in the state. From the data review, we know that aggravated assaults are the most abundant type of violent crime in the nation, so this being the only statistically significant results also helps support the statement that violent crime decreases after recreational marijuana legalization. There are other slightly significant results for overall violent and robbery crimes but only at the 90% confidence level. Interestingly enough, the counterfactual displays a future where violent crime in Nevada would have continued to increase if RMLs were not in place.

Table 13. NV vs UT, 2010 to 2019 Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	214.850***	1.900***	41.817***	42.417***	128.733***
	-17.875	-0.368	-3.699	-9.875	-9.07
treated	412.617***	3.700***	1.5	148.483***	258.967***
	-25.279	-0.521	-5.231	-13.966	-12.827
time	22.75	0.325	12.383*	0.583	9.417
	-28.263	-0.582	-5.848	-15.614	-14.341
didNVUT	-82.992*	1.075	11.525	-38.708*	-56.892**
	-39.97	-0.824	-8.271	-22.082	-20.281
Num.Obs.	20	20	20	20	20
R2	0.96	0.874	0.595	0.908	0.973
R2Adj.	0.952	0.85	0.519	0.89	0.968

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Now in regard to property crime, only larceny theft has a statistically significant DID estimator showing an increase of 269 cases per 100,000 people in Nevada after RMLs are enforced. Similarly, larceny theft is the most abundant type of property crime in the nation so with even with this being the only significant result we can say that property crime increases in Nevada after RMLs are passed. Also, the counterfactual here shows a mixture of decreases in property crime over time if RMLs were not passed.

Table 14. NV vs UT, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	2992.233***	454.933***	2297.150***	240.117***
	-75.994	-22.21	-50.286	-13.373
treated	-279.567**	334.883***	-740.650***	126.250***
	-107.472	-31.409	-71.115	-18.912
time	-422.608***	-106.508***	-343.300***	27.283
	-120.158	-35.116	-79.509	-21.144
didNVUT	199.767	-83.808	268.725**	14.725
	-169.929	-49.662	-112.443	-29.902
Num.Obs.	20	20	20	20
R2	0.574	0.923	0.905	0.845
R2Adj.	0.494	0.909	0.887	0.816

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Nevada and Idaho Comparison

Similar results are shown in the comparisons with Idaho in Tables 29 and 30 (shown in Appendix A). The DID estimator values do not change significantly for both aggravated assaults and larceny thefts. They do still show decreases in aggravated assaults and increases in larceny theft cases. Similar counterfactuals still apply as well. There is a statistically significant increase in rape cases however, I do not consider these results to be causal for the continuing reason of issues in the data. These results are not replicated in the robustness checks either (see appendix), further supporting the need to control for parallel trends in this DID model of effects from RMLs.

Oregon and Idaho Comparison

Results for the Oregon and Idaho model are found in Tables 15 and 16. The counterfactuals show an increase in violent crime and creases in property crime over time if RMLs were not passed in Oregon. Fortunately for us, they were passed and see statistically significant results for aggravated assaults, and motor vehicle thefts. Aggravated assaults increase by 17 cases per 100,000 people after legalization and motor vehicle thefts increase by 85 cases per 100,000 people. This is not entirely reflective of previous literature as there is an increase a violent related crime where we would have expected no effect or a decrease in cases. As this was seen in the Colorado comparisons as well, some of these effects not reflective of past findings are special to the specific treated state in the comparison.

Table 15. OR vs ID, 2010 to 2019 Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	211.800***	1.820***	33.760***	13.320***	162.920***
	-3.943	-0.153	-2.29	-1.24	-3.071
treated	34.900***	0.36	1.7	45.760***	-12.960***
	-5.576	-0.217	-3.239	-1.753	-4.343
time	12.840**	0.32	9.480***	-2.16	5.2
	-5.576	-0.217	-3.239	-1.753	-4.343
didOR	15.680*	0.02	-1.12	-0.44	17.260**
	-7.886	-0.306	-4.58	-2.479	-6.141
Num.Obs.	20	20	20	20	20
R2	0.903	0.396	0.492	0.988	0.653
R2Adj.	0.885	0.283	0.396	0.986	0.589

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 16. OR vs ID, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	1953.400***	421.380***	1441.860***	90.160***
	-66.223	-20.789	-46.451	-14.351
treated	1127.520***	91.600***	882.240***	153.720***
	-93.653	-29.4	-65.692	-20.296
time	-392.540***	-106.160***	-308.500***	22.12
	-93.653	-29.4	-65.692	-20.296
didOR	216.04	-0.28	131.68	84.580***
	-132.445	-41.578	-92.903	-28.702
Num.Obs.	20	20	20	20
R2	0.958	0.74	0.965	0.931
R2Adj.	0.951	0.691	0.959	0.918

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Washington and Idaho Comparison

To wrap this section up, Tables 17 show the results of the Washington and Idaho comparison. There is only one statistically significant result, and it is the DID estimator for robbery cases. With this result I can conclude there is a reduction in robbery cases by eight cases per 100,000 people in Washington after RMLs are passed. In the robustness check model using all available crime data, robbery cases still decrease with the addition of a statistically significant decrease in rape cases. This is peculiar because previously we would have seen an increase in rape cases because of the change in data reporting for that particular type of crime. This further supports the need to control for parallel trends in the models and a causal relationship between crime and marijuana legalization.

Table 17. WA vs ID, 2010 to 2019 Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	211.700***	1.775***	32.875***	13.525***	163.525***
	-4.752	-0.173	-1.847	-1.414	-3.725
treated	86.575***	0.725***	2.2	70.850***	12.800**
	-6.72	-0.245	-2.612	-2	-5.268
time	10.867*	0.342	9.375***	-2.142	3.325
	-6.135	-0.224	-2.385	-1.826	-4.809
didWA	-12.192	-0.025	-2.583	-7.617***	-2.017
	-8.676	-0.317	-3.372	-2.582	-6.801
Num.Obs.	20	20	20	20	20
R2	0.956	0.612	0.597	0.994	0.442
R2Adj.	0.948	0.54	0.522	0.993	0.337

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Colorado Comparisons Using Specific Area Approach

This final section of results will present the findings for all Colorado state comparisons now using specific metropolitan (urban) and non-metropolitan (rural) area crime data. The format will follow the same as the similar section in the first half of the results. All results are terms of estimated case totals provided by the FBI's Uniform Crime Report for each metropolitan and rural area of the corresponding states. I only analyze the models for the Colorado comparisons as there are more differences in the results for the four individual comparisons and there are enough comparisons to run four more additional models whereas in Nevada and the others would only provide two comparisons.

Colorado and Kansas, Metro and Rural Comparison

Results shown in Tables 18 and 19 show strong statistically significant evidence that property crime does increase after recreational marijuana legalization in Colorado. In both models for urban and rural areas every type of property crime except for one increases with statistical significance.

Table 18. Colorado vs Kansas (Metropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	63626.500***	12632.000***	45625.000***	5369.500***
	-2101.406	-576.743	-1316.494	-1065.204
treated	60772.250***	10932.750***	43982.000***	5857.500***
	-2971.837	-815.638	-1861.804	-1506.426
time	-6669.000**	-3373.333***	-3928.333**	632.667
	-2712.903	-744.572	-1699.587	-1375.173
didCO_KA	17050.083***	97.083	10615.500***	6337.500***
	-3836.625	-1052.984	-2403.579	-1944.788
Num.Obs.	20	20	20	20
R2	0.989	0.969	0.991	0.889
R2Adj.	0.987	0.963	0.99	0.869

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Larceny theft is still the most impactful crime for property related cases which is also seen in the state total comparison with Kansas and other models. In Tables 18 and 19, for violent crime cases, there is a statistically significant increase in rape cases but due to the issues with the data, this effect is taken with a grain of salt. There is a larger effect on property crime cases in metropolitan areas than in non-metropolitan areas of Colorado which is expected as most of the population is located there so more crimes are bound to occur. The robustness check however for these models does not match previous literature. In certain cases, there were decreases in property crime in rural areas thus leading to other assumptions that would contradict the main results and those of previous literature. As these models control for parallel trends, the results found here and in the next models are the most causal.

Table 19. Colorado vs Kansas (NonMetropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	4848.000***	1744.750***	2776.250***	327.000***
	-187.044	-99.953	-88.515	-21.406
treated	-1907.000***	-975.500***	-781.750***	-149.750***
	-264.52	-141.356	-125.18	-30.273
time	-891.333***	-393.750***	-550.083***	52.500*
	-241.473	-129.039	-114.273	-27.635
didCOKA	1102.667***	496.833**	530.583***	75.250*
	-341.494	-182.489	-161.606	-39.082
Num.Obs.	20	20	20	20
R2	0.814	0.808	0.782	0.774
R2Adj.	0.779	0.772	0.741	0.732

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Colorado and Nebraska, Metro and Rural Comparison

Tables 20, 21 and 22 show the results for this model and the effects somewhat match to the Kansas comparison model. This time every type of property crime has a statistically significant DID estimator in both metro and non-metro areas. All of these effects increase those cases except for burglaries in metro areas which shows a decrease of 3,219 cases in Colorado after RMLs. This one result along with the statistical significance of all violent crime cases in metro areas (Table 36), except for robbery cases, does not match previous literature. The increase in violent crime cases in Colorado’s metro areas is surprising, yet the only other comparison where we see this effect occur again is with Nebraska. So, there is a possibility that state specific effects from RMLs are still dependent on which state the treated variable is compared to. Additionally, the increase in violent crimes is only in metropolitan areas so the difference in population density could also be a factor. It is also possible that people who live in the rural areas travel to the busy urban areas and commit those violent or property crimes after marijuana legalization.

Table 20. Colorado vs Nebraska (Metropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	3891.000***	47.750***	469.000***	979.750***	2394.500***
	-619.28	-9.696	-131.046	-94.344	-443.636
treated	11022.500***	86.750***	1696.250***	2189.000***	7050.500***
	-875.794	-13.713	-185.327	-133.423	-627.396
time	524.667	-7.083	303.000*	-125.75	354.5
	-799.487	-12.518	-169.179	-121.798	-572.732
didCONE	2885.667**	51.583**	802.917***	401.333**	1629.833*
	-1130.646	-17.703	-239.256	-172.248	-809.965
Num.Obs.	20	20	20	20	20
R2	0.972	0.925	0.961	0.981	0.963
R2Adj.	0.966	0.911	0.953	0.978	0.957

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 21. Colorado vs Nebraska (Metropolitan Areas)

	Property	Burglary	Larceny Theft	Motorvehicle Theft
(Intercept)	36013.500***	6116.250***	26409.250***	3488.000***
	-2046.76	-473.08	-1272.354	-1066.964
treated	88385.250***	17448.500***	63197.750***	7739.000***
	-2894.555	-669.036	-1799.38	-1508.916
time	-3233.167	-1676.250**	-2152.083	595.167
	-2642.355	-610.743	-1642.601	-1377.445
didCONE	13614.250***	-1600.000*	8839.250***	6375.000***
	-3736.855	-863.721	-2322.989	-1948.002
Num.Obs.	20	20	20	20
R2	0.994	0.99	0.996	0.915
R2Adj.	0.993	0.988	0.995	0.899

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 22. Colorado vs Nebraska (NonMetropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	3254.000***	813.250***	2255.000***	185.750***
	-121.684	-55.339	-65.212	-20.489
treated	-313.000*	-44	-260.500**	-8.5
	-172.088	-78.261	-92.223	-28.976
time	-1139.167***	-275.250***	-883.000***	19.083
	-157.094	-71.442	-84.188	-26.452
didCO_NE	1350.500***	378.333***	863.500***	108.667**
	-222.164	-101.034	-119.059	-37.408
Num.Obs.	20	20	20	20
R2	0.825	0.657	0.89	0.676
R2Adj.	0.792	0.592	0.869	0.616

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Colorado and Utah, Metro and Rural Comparison

Before diving into the third of these models, the counterfactuals for this comparison show once again that violent crime would have increased while property crime decreased over time if RMLs were not passed. Based on the results in Tables 23 and 24, the models do match previous literature findings because of an increase in property crime cases. In metropolitan areas, there is a statistically significant increase in cases for every type of property crime except for burglaries. Non-metropolitan areas only see a statistically significant rise in burglaries, however. This is where our one prediction is seen which is why I choose to run these additional models.

For one, previous literature studying medical marijuana laws analyzed bordering states' counties. I choose not to do the same because the county crime data on the UCR crime reports, also used by this literature, had many missing county statistics across multiple years. To substitute this I used the provided metro and non-metro area crime reporting also on the same UCR dataset. The first main intention was to find parallels in previous literature still using this approach, which we have. However, because some crime specific effects are not statistically significant at the state level and then the national level, I made the prediction that differences in metro and non-metro areas cancel each other out, therefore lowering the effect of RMLs on crime.

Table 23. Colorado vs Utah (Metropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	79061.000***	12304.750***	60669.250***	6087.000***
	-2929.138	-597.59	-1968.649	-1111.549
treated	45337.750***	11260.000***	28937.750***	5140.000***
	-4142.427	-845.121	-2784.09	-1571.967
time	-2379.5	-1998.583**	-2097.25	1716.333
	-3781.501	-771.486	-2541.514	-1435.003
didCO_UT	12760.583**	-1277.667	8784.417**	5253.833**
	-5347.85	-1091.046	-3594.244	-2029.401
Num.Obs.	20	20	20	20
R2	0.963	0.962	0.96	0.855
R2Adj.	0.956	0.955	0.953	0.828

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 24. Colorado vs Utah (NonMetropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	2533.000***	586.250***	1796.750***	150.000***
	-138.772	-39.245	-106.615	-24.024
treated	408.000*	183.000***	197.75	27.25
	-196.253	-55.501	-150.777	-33.974
time	-85.667	-136.250**	-31.917	82.500**
	-179.154	-50.666	-137.64	-31.014
didCOUT	297	239.333***	12.417	45.25
	-253.362	-71.652	-194.652	-43.861
Num.Obs.	20	20	20	20
R2	0.599	0.86	0.227	0.656
R2Adj.	0.524	0.833	0.082	0.591

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

In the state total model for the Colorado and Utah comparison, not one crime category showed a statistically significant DID estimator meaning no effect on crime. When we split areas, burglary cases decrease in metro areas though not statistically significant. In Colorado's rural areas the effect is now significant and with an increase in cases. From here I conclude that when the state crime level is estimated, these spatial differences are canceled out if there is a slight difference in the effect from RMLs.

Colorado and Wyoming, Metro and Rural Comparison

For the final model of this paper, the results are in Tables 25, 26, and 27. Similar to the findings found in the Colorado and Nebraska comparison model, the statistically significant results for effects on crime in metropolitan areas increase for all types except for robberies. In non-metropolitan areas all types of property crime increase.

Table 25. Colorado vs Wyoming (Metropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	374.25	4	46.5	42.25	281.5
	-611.969	-9.475	-123.483	-87.246	-437.35
treated	14539.250***	130.500***	2118.750***	3126.500***	9163.500***
	-865.456	-13.4	-174.631	-123.384	-618.507
time	58.75	2.833	33.167	0.75	22
	-790.049	-12.232	-159.415	-112.634	-564.617
didCO_WY	3351.583***	41.667**	1072.750***	274.833	1962.333**
	-1117.298	-17.299	-225.447	-159.288	-798.489
Num.Obs.	20	20	20	20	20
R2	0.983	0.956	0.977	0.991	0.978
R2Adj.	0.98	0.948	0.972	0.989	0.974

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

If recreational marijuana laws had not been passed in Colorado, the counterfactuals of the model show that violent crime would still have increased but most property crime would have decreased. Just like in every one of these models, these results also show an increase in rape cases but because of the issue with the data set on case reporting changes, this is the one effect I do not conclude to be causal of the 9 different types of crime.

Table 26. Colorado vs Wyoming (Metropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	5172.250**	841.000*	4093.000***	238.25
	-1925.429	-405.447	-1188.498	-1058.251
treated	119226.500***	22723.750***	85514.000***	10988.750***
	-2722.968	-573.389	-1680.79	-1496.593
time	-474.25	-57.167	-533	115.917
	-2485.718	-523.43	-1534.344	-1366.196
didCO_WY	10855.333***	-3219.083***	7220.167***	6854.250***
	-3515.337	-740.242	-2169.89	-1932.093
Num.Obs.	20	20	20	20
R2	0.997	0.995	0.998	0.946
R2Adj.	0.996	0.994	0.997	0.936

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 27. Colorado vs Wyoming (NonMetropolitan Areas)

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	1506.250***	337.250***	1082.000***	87.000***
	-82.3	-37.214	-40.787	-19.497
treated	1434.750***	432.000***	912.500***	90.250***
	-116.39	-52.629	-57.682	-27.572
time	-380.917***	-114.250**	-280.833***	14.167
	-106.249	-48.043	-52.656	-25.17
didCOWY	592.250***	217.333***	261.333***	113.583***
	-150.259	-67.943	-74.467	-35.596
Num.Obs.	20	20	20	20
R2	0.974	0.949	0.982	0.872
R2Adj.	0.97	0.939	0.979	0.847

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Summary of DID State Comparison Models

The strongest results that reflect previous literature findings are those for the Colorado comparisons. In both the state total and area-specific approaches, property crime cases increase with statistical significance. Only in one state comparison of Colorado does murder and robbery cases increase. On the other hand, in two of the area-specific models are there increases in most violent crime cases and only for Colorado's metropolitan areas. Even though almost every model shows a positive effect on rape cases, as mentioned before, this is the one result I do not consider to be causal. These models control for parallel trends, state differences by using cross border analysis, and match previous literature as the main effect on crime from recreational marijuana laws is increases in property crimes, all other results are considered to be causal. There is, however, a concern that should be touched upon in future literature.

The other state comparison models do not all share the same results. In the Washington and Idaho comparison robbery cases are statistically significantly reduced by RMLs. For Oregon, aggravated assault cases increase and only motor vehicle thefts increase. In Nevada the effect on aggravated assaults is now a reduction in cases and only larceny theft crimes increase. Because of these key differences, it is also important to conclude that the effect of RMLs can differ from state to state even though we controlled for state differences. Part of the reason could be due to each state being exposed to RMLs for different lengths of time so far and some details of RMLs themselves differ by state. Future literature should be tasked in separating these potential effects at a state level.

CHAPTER 7

DIFFERENCES BETWEEN THE NATIONAL AND STATE TOTALS RESULTS

Before providing my final conclusion for these analyses, there are some key differences in the results between the national and state models. At a national level, using rollout group effect aggregation we found that murder, rape, larceny theft, and total property crime cases are statistically significantly affected by RMLs with the only negative effect being on murder cases. For the national model aggregating the effect by length of exposure to RMLs we found that only murder and rape cases are statistically significantly affected by RMLs with again another decreasing effect on murder cases. Seeing an effect on larceny theft cases for the national model is no surprise as it is the most abundant type of property crime in the county nation but there was no statistically significant evidence for effects on aggravated assaults which is the most common type of violent crime. For the state level models, the results can change depending on the state comparison.

For most of the Colorado comparisons, there was an increase in property crimes except for burglaries and only one result showing an increase in robbery and murder cases. The Washington and Oregon comparison models have decreases in robbery cases and rises in aggravated assault and motor vehicle theft crimes. Results for the Nevada comparisons do match what we would expect to definitely be affected by RMLs. The results show reductions in aggravated assaults in Nevada and a rise in larceny theft cases.

One of the main differences from these results is that at a national level there is no effect on the most common type of violent crime, aggravated assaults, but at a state level, there is. At a state level, there is also an increase in motor vehicle theft cases, robbery, and murder cases but not all in the same comparisons. Still, these effects are not seen at a national level wherefrom these three we only have evidence for a reduction in murder cases. The only reductions in violent crime at the state level are for aggravated assault and robbery cases. From this, I conclude the models that closely represent previous literature are the national ones using Group Time Average Treatment Effects. Keep in mind, the evidence found in previous literature only analyze cross border effects and geospatial census tracts. Although some state comparison models match previous literature, to name a few two of the Colorado models and the Washington model, because of some minor changes I conclude that as a state total effect they do not match previous literature findings. because of this difference, I believe that although the main effects of recreational marijuana laws increase property crime rates, other effects on crime are to be expected, such as reductions in some violent crimes or no effect on them at all. Future literature further explores this by finding a way to control for the legalization differences per state which could be contributing to the differing results I found at the national and state levels.

CHAPTER 8

CONCLUSION

In this paper I asked the question, did the legalization of recreational marijuana laws affect crime rates in the U.S. Previous literature had studied the effect of both medical and recreational marijuana laws finding evidence that violent crimes go unaffected but statistically significant evidence found says property crimes are positively affected. Applying the same FBI UCR data set used in most of those studies and the widely adopted DID model, I approached the question a bit differently by analyzing all treated states against the rest of the U.S in both group and event study models, specific state comparisons, and urban/rural area-specific comparisons for Colorado and its untreated neighbors. The parallel trends assumption is not met for property crime and to maintain the integrity of the DID model I control for parallel trends by only using data from 2010 to 2019 for my main models. I do rerun each model using all available crime statistics from the UCR dataset, which includes the years 1999 to 2019, as a robustness check to the models. For clarity, this section will be split into three final parts first with a short summary of the robustness checks, following with the conclusion for the main results, and finally with a closing summary.

Results of the Robustness Checks

For the robustness check of the national models, the results do not change from the main model. The differences are seen heavily in the individual state comparisons. Most of those results do not match previous literature and in some types of crime, there are changes in statistical significance. It is possible that at a national level, there is a stronger control for state differences because we analyze all 50 states, so the parallel trends assumption is maintained but only in this case. At the state level, the differences in the results really do show the need to control for parallel trends. With this in mind, I believe the robustness checks further support that the main models are the most causal method to finding the effect on crime from marijuana legalization.

Conclusion for Main Results

The GTAFE results using the data set from 2010 to 2019 for the national models have results where overall violent crime is unaffected but overall property crimes are positively affected by RMLs with statistical significance. There is also evidence of a reduction in murder cases and a rise in larceny theft cases. When estimating the GTAFE model by length of exposure to RMLs, the only crime with statistically significant evidence that they are affected is murder cases. The magnitude of that effect is roughly the same with a reduction in 5.7% of cases with respect to the national average.

Combining the results of the four Colorado comparisons, the results for property crimes accurately match previous literature with increases in cases with statistical significance. However, in the comparison with Nebraska, there are statistically significant increases in murder and robbery cases not seen in previous studies. The Nevada comparison models have results showing statistically significant decreases in aggravated assault cases and increases in larceny theft. These effects are reflective of other findings but there is also an increase in rape cases showing statistical significance, but this could be coming from the counting change in the UCR dataset. The results from the Washington to Idaho comparison show a statistically significant decrease in robbery cases and the Oregon to Idaho comparison results show two statistically significant increases in aggravated assault and motor vehicle thefts cases.

Results for the area specific comparisons of Colorado and its bordering states are also reflective of previous literature. The urban results differ in some crimes as the results reflect increases in property related crimes, but some types of violent crimes are affected by RMLs including rape which again could be from the circumstantial bias of the dataset. But the results for the rural areas models reflect previous literature with only increases in property crimes with the exemption of the increase in rape cases.

Closing Summary

Based on the results of my study, there are a couple final conclusions I can state. When observing the effect of RMLs in some states on crime in the U.S as a country, there is no effect on violent crime except for reductions in murder cases but there are increases in overall property crime and specifically larceny theft cases. If the next area of interest is how RMLs affect crime in individual states the results can differ a bit when it comes to violent crime categories, but one can expect increases in property crimes. Finally, when observing effects in metropolitan and non-metropolitan areas, RMLs will have positive effects on violent crimes in metro areas and positive effects on property crimes in both. In some models, there is an additional negative effect on violent crimes in non-metro areas, but these area specific conclusions are from the Colorado comparisons only.

From these findings, one can argue that the legalization of RMLs has had a positive effect on society by reducing the number of violent crimes in those states if you also take into consideration findings from previous literature. On the other hand, the increases in property crimes can be worrisome and now that this study and many others have found those same effects to be causal, pundits should take future steps in trying to reduce that effect. The solution would not be to roll back RMLs but perhaps improve the law. For example, the legalization details of marijuana vary by state to some extent and some states might already have some demographic crime issues not relevant to marijuana. There is also the issue of western migration, although in the last two years that rate has slowed down drastically. The difference in population in the western states with RMLs and other economic effects from the migration, like an increase in poverty rates, could also be affecting crime. In the national level models, it seems we controlled for those state differences by including every state but in the individual state comparisons, some increases in crime may be coming from these exogenous effects that cannot be controlled for in just two states. So, future research is needed to find a proper solution to increase the benefit to society from marijuana legalization as so far there are some tradeoffs to having it legalized now.

Recommendations for Future Literature

One limitation of this paper is in the data available. The earliest year when recreational marijuana sales began after RML rollouts is in 2014. The FBI UCR data set only has crime data until 2019. This gives us five years after the treatment year to analyze the effect of RMLs so as of now this study would only identify the short-run causal effect of RMLs and future research will have to study the long-run effects. In addition, because of the COVID-19 pandemic, future research will have trouble controlling for changes in crime from this world event just like the effect from the 2008 stock market crash which is most likely the reason why the parallel trends assumption was not met for property crimes. These will be easy to control for in a national model but at the state level could be troublesome. If future research can control for parallel trends without having to drop certain years from the data set and run robustness checks, that would greatly enhance the supporting evidence for future results. Lastly, the redefinition of rape in the FBI's crime reporting, although influential and essential in accurately reporting cases in the U.S, is a limitation to this study as the jump in counted cases begins in 2013 close to the earliest rollout year of RMLs. So, the effects on rape cases in this study could be skewed and future literature will need to find a way to control for this change.

APPENDIX A

MAIN MODELS NOT SHOWN IN BODY OF PAPER

These models have statistically significant results but were not shown in the body of the paper as they were deemed redundant, and their omission reduced the length of the paper. They did not however reduce the quality of the content of the paper. Models with statistically insignificant results are not shown.

Table 28. CO vs UT, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	3023.725***	480.500***	2317.650***	225.525***
	-99.333	-21.566	-72.33	-21.328
treated	-365.300**	20.475	-387.850***	2.1
	-140.478	-30.499	-102.291	-30.163
time	-334.225**	-113.617***	-263.033**	42.508
	-128.238	-27.842	-93.378	-27.535
didCONE	321.833*	17.625	234.900*	69.267*
	-181.356	-39.374	-132.057	-38.94
Num.Obs.	20	20	20	20
R2	0.398	0.661	0.585	0.601
R2Adj.	0.285	0.597	0.508	0.526

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 29. NV vs ID, 2010 to 2019 Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	212.433***	1.833***	35.117***	13.033	162.450***
	-17.645	-0.38	-3.094	-9.777	-9.037
treated	415.033***	3.767***	8.200*	177.867***	225.250***
	-24.953	-0.537	-4.376	-13.826	-12.78
time	14.467	0.367	8.458	-1.983	7.675
	-27.899	-0.601	-4.892	-15.458	-14.289
didNVID	-74.708*	1.033	15.450**	-36.142	-55.150**
	-39.454	-0.849	-6.919	-21.862	-20.207
Num.Obs.	20	20	20	20	20
R2	0.962	0.87	0.737	0.937	0.964
R2Adj.	0.955	0.845	0.688	0.925	0.958

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 30. NV vs ID, 2010 to 2019 Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	1918.467***	412.817***	1411.667***	93.983***
	-59.881	-20.118	-40.073	-8.465
treated	794.200***	377.000***	144.833**	272.383***
	-84.685	-28.452	-56.672	-11.971
time	-403.342***	-111.292***	-310.142***	18.092
	-94.68	-31.81	-63.361	-13.384
didNVID	180.5	-79.025*	235.567**	23.917
	-133.898	-44.986	-89.606	-18.927
Num.Obs.	20	20	20	20
R2	0.925	0.948	0.775	0.983
R2Adj.	0.911	0.939	0.732	0.98

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 31. Colorado vs Kansas (Metropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	7429.000***	78.000***	749.500***	1275.500***	5326.000***
	-673.99	-10.959	-129.158	-103.39	-513.211
treated	7484.500***	56.500***	1415.750***	1893.250***	4119.000***
	-953.166	-15.499	-182.657	-146.215	-725.789
time	1335.333	14	340.000*	121.833	859.5
	-870.118	-14.149	-166.742	-133.475	-662.552
didCO_KA	2075	30.5	765.917***	153.75	1124.833
	-1230.533	-20.009	-235.809	-188.763	-936.99
Num.Obs.	20	20	20	20	20
R2	0.934	0.812	0.951	0.967	0.882
R2Adj.	0.922	0.777	0.942	0.961	0.86

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 32. Colorado vs Kansas (NonMetropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	674.500***	11.500***	85.250***	15.000***	562.750***
	-43.358	-2.06	-10.575	-3.291	-35.212
treated	-252.750***	-3	-27.000*	-6.5	-216.250***
	-61.317	-2.914	-14.956	-4.654	-49.797
time	49	-2.667	2.083	4.333	45.25
	-55.975	-2.66	-13.653	-4.249	-45.458
didCOKA	45.083	3.333	66.500***	5.333	-30.083
	-79.16	-3.762	-19.308	-6.009	-64.287
Num.Obs.	20	20	20	20	20
R2	0.701	0.078	0.629	0.318	0.779
R2Adj.	0.645	-0.094	0.559	0.191	0.738

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 33. Colorado vs Wyoming (NonMetropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	194.000***	3.250*	24.500**	5.75	160.500***
	-42.534	-1.805	-9.671	-3.673	-35.58
treated	227.750***	5.250*	33.750**	2.75	186.000***
	-60.152	-2.553	-13.677	-5.194	-50.318
time	84.833	-0.25	19.833	-0.917	66.167
	-54.911	-2.331	-12.485	-4.742	-45.934
didCOWY	9.25	0.917	48.750**	10.583	-51
	-77.656	-3.296	-17.657	-6.706	-64.96
Num.Obs.	20	20	20	20	20
R2	0.728	0.448	0.843	0.426	0.619
R2Adj.	0.678	0.345	0.813	0.318	0.548

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 34. Colorado vs Utah (Metropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	5358.250***	39.500***	923.000***	1148.000***	3247.750***
	-625.211	-9.708	-136.696	-98.956	-445.29
treated	9555.250***	95.000***	1242.250***	2020.750***	6197.250***
	-884.182	-13.729	-193.317	-139.945	-629.735
time	1131.75	18.167	558.667***	160.5	394.417
	-807.144	-12.533	-176.473	-127.752	-574.866
didCO_UT	2278.583*	26.333	547.250**	115.083	1589.917*
	-1141.474	-17.724	-249.571	-180.668	-812.984
Num.Obs.	20	20	20	20	20
R2	0.962	0.917	0.931	0.972	0.954
R2Adj.	0.954	0.902	0.918	0.967	0.946

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 35. Colorado vs Utah (NonMetropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	264.000***	4.500**	38.000***	9.000**	212.500***
	-44.688	-2.014	-10.151	-3.533	-35.075
treated	157.750**	4	20.25	-0.5	134.000**
	-63.199	-2.849	-14.356	-4.996	-49.603
time	72.333	2.333	28.500**	0.833	40.667
	-57.692	-2.6	-13.105	-4.561	-45.282
didCOUT	21.75	-1.667	40.083**	8.833	-25.5
	-81.589	-3.678	-18.534	-6.45	-64.038
Num.Obs.	20	20	20	20	20
R2	0.584	0.185	0.778	0.299	0.488
R2Adj.	0.506	0.033	0.736	0.168	0.392

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

Table 36. Colorado vs Nebraska (NonMetropolitan Areas)

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	215.250***	3.750**	50.000***	8.750**	152.750***
	-41.723	-1.656	-9.594	-3.326	-33.515
treated	206.500***	4.750*	8.25	-0.25	193.750***
	-59.006	-2.341	-13.568	-4.703	-47.397
time	86.583	1.083	17.5	-1.417	69.417
	-53.865	-2.137	-12.386	-4.294	-43.268
didCO_NE	7.5	-0.417	51.083**	11.083*	-54.25
	-76.176	-3.023	-17.516	-6.072	-61.19
Num.Obs.	20	20	20	20	20
R2	0.702	0.375	0.769	0.38	0.664
R2Adj.	0.646	0.258	0.725	0.264	0.601

Note: * p < 0.1, ** p < 0.05, *** p < 0.01

APPENDIX B

ROBUSTNESS CHECKS

Only tables with statistically significant results are shown. Other tables of the robustness check not shown do not have any statistically significant results.

Table 37. Summary of ATT's based on group/ cohort aggregation: Robustness Check

Murder Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	-0.262**		0.0971	-0.4524	-0.0717
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	-0.276	0.1889	-0.7333	0.1814
	2015	-0.1605	0.1241	-0.461	0.14
	2016	-0.443**	0.1278	-0.7524	-0.1336
	2017	-0.6403**	0.0905	-0.8594	-0.4212
	2018	-0.0192	0.1151	-0.2979	0.2595
Rape Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	4.9666**		1.8687	1.3041	8.6291
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	2.3773	1.7804	-1.761	6.5156
	2015	2.4651**	0.8226	0.553	4.3773
	2016	17.4791**	0.9584	15.2514	19.7067
	2017	8.8279**	0.9175	6.6952	10.9606
	2018	0.6198	0.6944	-0.9942	2.2337

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 38. Summary of ATT's based on group/ cohort aggregation: Robustness Check

Larceny Theft Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	121.9102**		45.0395	33.6344	210.186
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	78.2467**	74.262	-81.5682	238.0616
	2015	115.5498**	17.5571	77.7661	153.3334
	2016	349.9913**	24.4411	297.393	402.5896
	2017	130.1612	12.963	102.2643	158.0581
	2018	50.5878	38.4055	-32.0623	133.2379
Motor Vehicle Theft Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	29.949		25.5573	-20.1425	80.0404
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	25.1886**	42.6454	-66.6048	116.9819
	2015	89.353**	5.9801	76.4809	102.2251
	2016	175.2145**	4.2092	166.1544	184.2747
	2017	-52.1868**	3.0495	-58.7509	-45.6228
	2018	-26.5576	11.4298	-51.16	-1.9551

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 39. Summary of ATT's based on group/ cohort aggregation: Robustness Check

Total Violent Crime Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	1.3777		7.0563	-12.4525	15.2078
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	11.637**	15.0225	-21.3347	44.6087
	2015	22.5544**	6.6025	8.0631	37.0457
	2016	106.3744**	5.3176	94.7032	118.0456
	2017	-139.3488	4.6943	-149.6519	-129.0457
	2018	-1.6052	8.2585	-19.7311	16.5207
Total Property Crime Cases	ATT		Std. Error	[95% Simult. Conf. Int]	
	198.0355**		96.3512	9.1907	386.8803
Group Effects	Group	Estimate	Std. Error	[95% Simult. Conf. Band]	
	2014	118.4351**	161.509	-385.943	622.8132
	2015	282.82**	29.8534	189.5905	376.0495
	2016	661.8721**	26.8068	578.157	745.5872
	2017	108.7062	18.5206	50.868	166.5444
	2018	47.9901	34.6533	-60.229	156.2093

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 40. Summary of ATT's based on event-study/dynamic aggregation: Robustness Check

	ATT		Std. Error	[95% Conf. Int]	
Murder Cases	-0.2812**		0.1212	-0.5187	-0.0437
	Event time	Estimate	Std. Error	[95% Simult. Conf. Band]	
Dynamic Effects	-18	0.3756**	0.1241	0.0794	0.6717
	-17	-0.5302	0.8621	-2.5874	1.5269
	-16	-0.2692	1.3609	-3.5167	2.9784
	-15	0.1163	0.5349	-1.1602	1.3928
	-14	-0.0219	0.2658	-0.6563	0.6124
	-13	-0.0671	0.2798	-0.7347	0.6005
	-12	0.1382	0.1944	-0.3258	0.6022
	-11	-0.1226	0.2478	-0.7139	0.4687
	-10	-0.1355	0.3064	-0.8667	0.5956
	-9	-0.088	0.2415	-0.6643	0.4882
	-8	-0.4236	0.2842	-1.1018	0.2547
	-7	-0.2086	0.1606	-0.5919	0.1746
	-6	0.1017	0.2904	-0.5914	0.7947
	-5	0.0286	0.1948	-0.4364	0.4935
	-4	-0.0306	0.3643	-0.8999	0.8387
	-3	0.1276	0.179	-0.2995	0.5547
	-2	0.101	0.1849	-0.3403	0.5422
	-1	0.4578	0.3251	-0.318	1.2336
	0	-0.0223	0.3096	-0.761	0.7164
	1	-0.2063	0.1176	-0.487	0.0744
	2	-1.1763	0.5095	-2.392	0.0395
	3	0.0436	0.3991	-0.9088	0.996
	4	0.0752	0.2043	-0.4124	0.5628
	5	-0.4012	0.2064	-0.8937	0.0914

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 41. Summary of ATT's based on event-study/dynamic aggregation: Robustness Check

	ATT		Std. Error	[95% Conf. Int]	
Rape Cases	5.0549**		2.521	0.1139	9.9959
	Event time	Estimate	Std. Error	[95% Simult. Conf. Band]	
Dynamic Effects	-18	0.7593	0.7551	-1.0178	2.5364
	-17	-1.6543	3.3568	-9.5545	6.246
	-16	-2.057**	0.7146	-3.7389	-0.3751
	-15	0.36	0.3844	-0.5446	1.2646
	-14	-1.2844	0.5672	-2.6193	0.0505
	-13	2.1412	2.4697	-3.6714	7.9538
	-12	-0.7774	1.5109	-4.3334	2.7786
	-11	-0.4276	0.8418	-2.4088	1.5537
	-10	-0.6947	0.841	-2.674	1.2847
	-9	-0.1419	0.5873	-1.524	1.2403
	-8	-1.8645	2.4728	-7.6842	3.9553
	-7	-0.3664	2.1158	-5.3461	4.6132
	-6	0.2189	0.6904	-1.406	1.8438
	-5	-1.2239	3.1833	-8.7159	6.2681
	-4	3.8243	3.8021	-5.1241	12.7726
	-3	3.4801	7.2747	-13.6412	20.6013
	-2	-1.0336	4.5427	-11.7249	9.6578
	-1	0.8472	3.1002	-6.4492	8.1436
	0	3.9233	3.2494	-3.7242	11.5707
	1	0.8053	3.3013	-6.9645	8.5751
	2	11.3009	7.6794	-6.7728	29.3747
	3	8.9215	4.7153	-2.1761	20.0191
	4	3.6853	3.3595	-4.2215	11.5921
	5	1.693	2.3113	-3.7467	7.1327

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 42. Colorado vs Kansas: All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	387.793***	4.140***	39.553***	66.967***	277.133***
	-7.556	-0.197	-0.977	-2.506	-6.079
treated	-43.067***	-0.660**	4.187***	5.913	-52.527***
	-10.686	-0.278	-1.382	-3.544	-8.597
time	9.157	-0.09	11.697***	-12.717***	10.267
	-14.136	-0.368	-1.829	-4.688	-11.373
didCOKA	-0.717	0.127	9.247***	3.17	-13.257
	-19.992	-0.521	-2.586	-6.63	-16.084
Num.Obs.	42	42	42	42	42
R2	0.384	0.158	0.844	0.305	0.616
R2Adj.	0.336	0.091	0.832	0.25	0.586

Note: * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01

Table 43. Colorado vs Wyoming: All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	234.147***	2.413***	28.913***	14.687***	188.127***
	-6.626	-0.136	-1.351	-1.405	-5.585
treated	110.580***	1.067***	14.827***	58.193***	36.480***
	-9.37	-0.193	-1.911	-1.987	-7.899
time	-12.663	0.237	10.720***	-2.803	-20.793*
	-12.396	-0.255	10.720***	-2.629	-10.449
didCOWY	21.103	-0.2	10.223***	-6.743*	17.803
	-17.53	-0.361	-3.575	-3.718	-14.777
Num.Obs.	42	42	42	42	42
R2	0.852	0.508	0.845	0.968	0.53
R2Adj.	0.84	0.469	0.833	0.965	0.493

Note: * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01

Table 44. Colorado vs Wyoming: All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	2870.267***	438.220***	2300.867***	131.173***
	-113.519	-18.041	-80.497	-20.85
treated	445.807***	174.980***	32.34	238.487***
	-160.54	-25.514	-113.84	-29.487
time	-1035.067***	-159.487***	-868.350***	-7.223
	-212.374	-33.751	-150.597	-39.008
didCOWY	365.027	-48.73	436.810**	-23.037
	-300.343	-47.732	-212.976	-55.165
Num.Obs.	42	42	42	42
R2	0.569	0.754	0.537	0.697
R2Adj.	0.535	0.734	0.501	0.673

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 45. Washington vs Idaho: All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	235.347***	2.027***	35.513***	16.453***	181.340***
	-5.087	-0.113	-1.104	-1.149	-3.506
treated	99.207***	0.840***	5.913***	77.060***	15.400***
	-7.194	-0.159	-1.561	-1.625	-4.958
time	-12.78	0.09	6.737***	-5.070**	-14.490**
	-9.517	-0.211	-2.065	-2.15	-6.559
didWA	-24.823*	-0.14	-6.297**	-13.827***	-4.617
	-13.459	-0.298	-2.921	-3.041	-9.276
Num.Obs.	42	42	42	42	42
R2	0.867	0.483	0.349	0.987	0.394
R2Adj.	0.856	0.442	0.298	0.986	0.346

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 46. Nevada vs Idaho: All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	232.824***	2.018***	35.994***	15.935**	178.865***
	-11.967	-0.278	-1.351	-5.976	-9.229
treated	404.771***	5.006***	6.859***	203.988***	188.941***
	-16.924	-0.393	-1.911	-8.451	-13.052
time	-5.924	0.182	7.581**	-4.885	-8.74
	-27.42	-0.637	-3.095	-13.692	-21.147
didNVID	-64.446	-0.206	16.791***	-62.263***	-18.841
	-38.778	-0.901	-4.378	-19.363	-29.906
Num.Obs.	42	42	42	42	42
R2	0.946	0.838	0.729	0.946	0.869
R2Adj.	0.942	0.826	0.708	0.941	0.858

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 47. Nevada vs Utah: All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	229.224***	1.988***	38.547***	48.047***	140.653***
	-12.034	-0.271	-1.584	-6.04	-9.225
treated	408.371***	5.035***	4.306*	171.876***	227.153***
	-17.018	-0.383	-2.24	-8.542	-13.046
time	8.376	0.237	15.653***	-5.047	-2.503
	-27.573	-0.62	-3.63	-13.84	-21.137
didNVUT	-78.746*	-0.26	8.719*	-62.101***	-25.078
	-38.994	-0.877	-5.133	-19.573	-29.892
Num.Obs.	42	42	42	42	42
R2	0.946	0.847	0.656	0.923	0.905
R2Adj.	0.942	0.834	0.629	0.917	0.897

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 48. Colorado vs Kansas (Metropolitan Areas): All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	7757.154***	666.769	1260.308*	2060.000***	5545.615***
	-338.702	-813.32	-733.96	-660.52	-428.295
treated	7067.313***	585.764	1605.159	2155.200**	4288.051***
	-462.755	-1111.207	-1002.78	-902.442	-585.163
time	1007.179	-574.769	-170.808	-662.667	639.885
	-602.725	-1447.313	-1306.091	-1175.404	-762.157
didCO_KA	2492.187***	-498.764	576.508	-108.2	955.782
	-843.361	-2025.15	-1827.545	-1644.682	-1066.447
Num.Obs.	40	40	40	40	40
R2	0.924	0.026	0.113	0.197	0.718
R2Adj.	0.918	-0.055	0.04	0.13	0.694

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 49. Colorado vs Kansas (NonMetropolitan Areas): All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	5876.000***	1883.308***	3677.923***	443.692***
	-418.779	-84.904	-285.436	-31.72
treated	-2037.133***	-1004.574***	-929.256**	-154.092***
	-572.161	-116.001	-389.98	-43.338
time	-1919.333**	-532.308***	-1451.756***	-64.192
	-745.222	-151.087	-507.937	-56.446
didCOKA	1232.8	525.908**	678.09	79.592
	-1042.751	-211.409	-710.73	-78.982
Num.Obs.	40	40	40	40
R2	0.347	0.708	0.295	0.282
R2Adj.	0.292	0.683	0.237	0.222

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 50. Colorado vs Wyoming (Metropolitan Areas): All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	354.267	24.933	72.533	62.133	257.867
	-277.217	-670.385	-602.866	-544.052	-355.397
treated	14470.200***	1227.6	2792.933***	4153.067***	9575.800***
	-392.044	-948.068	-852.582	-769.406	-502.607
time	78.733	-18.1	7.133	-19.133	45.633
	-518.626	-1254.176	-1127.859	-1017.828	-664.887
didCO_WY	3420.633***	-1055.433	398.567	-751.733	1550.033
	-733.448	-1773.673	-1595.034	-1439.427	-940.292
Num.Obs.	42	42	42	42	42
R2	0.983	0.052	0.302	0.495	0.937
R2Adj.	0.982	-0.023	0.246	0.455	0.932

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 51. Colorado vs Wyoming (Metropolitan Areas): All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	5369.2	883.533	4245.133	282.667
	-5507.433	-557.463	-3534.25	-787.412
treated	124256.467***	24342.267***	86416.800***	15683.533***
	-7788.686	-788.371	-4998.184	-1113.569
time	-671.2	-99.7	-685.133	71.5
	-10303.463	-1042.917	-6611.976	-1473.113
didCO_WY	5825.367	-4837.600***	6317.367	2159.467
	-14571.297	-1474.908	-9350.746	-2083.297
Num.Obs.	42	42	42	42
R2	0.906	0.97	0.92	0.888
R2Adj.	0.899	0.967	0.914	0.88

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 52. Colorado vs Wyoming (NonMetropolitan Areas): All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	1779.000***	390.933***	1301.400***	124.800***
	-219.649	-28.169	-162.048	-19.118
treated	2059.867***	487.800***	1447.267***	164.800***
	-310.631	-39.838	-229.171	-27.037
time	-653.667	-167.933***	-500.233	-23.633
	-410.926	-52.7	-303.165	-35.767
didCOWY	-32.867	161.533**	-273.433	39.033
	-581.137	-74.529	-428.74	-50.582
Num.Obs.	42	42	42	42
R2	0.636	0.873	0.609	0.612
R2Adj.	0.607	0.863	0.578	0.581

Note: * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01

Table 53. Colorado vs Utah (Metropolitan Areas): All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	5236.933***	384.667	1105.267*	1469.667**	3314.533***
	-285.338	-701.848	-628.638	-567.692	-367.467
treated	9587.533***	867.867	1760.200*	2745.533***	6519.133***
	-403.528	-992.563	-889.029	-802.837	-519.676
time	1253.067**	-327	376.4	-161.167	327.633
	-533.818	-1313.038	-1176.075	-1062.054	-687.467
didCO_UT	2246.300***	-746.533	29.3	-609.7	1268.033
	-754.933	-1856.916	-1663.221	-1501.971	-972.225
Num.Obs.	42	42	42	42	42
R2	0.961	0.034	0.132	0.282	0.869
R2Adj.	0.958	-0.042	0.063	0.225	0.858

Note: * *p* < 0.1, ** *p* < 0.05, *** *p* < 0.01

Table 54. Colorado vs Utah (NonMetropolitan Areas): All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	245.467***	17.4	54.400**	24	191.667***
	-19.879	-24.901	-22.737	-24.62	-18.067
treated	254.000***	27.867	39.6	26.467	235.267***
	-28.114	-35.215	-32.155	-34.818	-25.55
time	90.867**	-10.567	12.1	-14.167	61.500*
	-37.191	-46.585	-42.536	-46.06	-33.799
didCOUT	-74.5	-25.533	20.733	-18.133	-126.767**
	-52.596	-65.881	-60.156	-65.139	-47.8
Num.Obs.	42	42	42	42	42
R2	0.729	0.029	0.084	0.028	0.708
R2Adj.	0.707	-0.048	0.012	-0.048	0.685

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 55. Colorado vs Nebraska (Metropolitan Areas): All Data

	Violent	Murder	Rape	Robbery	Agg. Assault
(Intercept)	4281.733***	313.733	620.333	1274.200**	2893.667***
	-292.56	-690.087	-621.643	-557.858	-370.635
treated	10542.733***	938.8	2245.133**	2941.000***	6940.000***
	-413.743	-975.93	-879.136	-788.931	-524.157
time	133.933	-273.067	151.667	-420.2	-144.667
	-547.33	-1291.034	-1162.987	-1043.658	-693.395
didCONE	3365.433***	-800.467	254.033	-350.667	1740.333*
	-774.042	-1825.798	-1644.713	-1475.955	-980.609
Num.Obs.	42	42	42	42	42
R2	0.967	0.037	0.206	0.332	0.883
R2Adj.	0.965	-0.039	0.143	0.279	0.874

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 56. Colorado vs Nebraska (Metropolitan Areas): All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	37607.933***	6098.067***	27911.067***	4145.600***
	-5737.275	-570.716	-3721.277	-798.334
treated	92017.733***	19127.733***	62750.867***	11820.600***
	-8113.732	-807.114	-5262.68	-1129.014
time	-4827.6	-1658.067	-3653.9	-62.433
	-10733.458	-1067.711	-6961.871	-1493.546
didCONE	9981.767	-3279.233**	9286.133	2293.4
	-15179.402	-1509.972	-9845.572	-2112.193
Num.Obs.	42	42	42	42
R2	0.835	0.951	0.851	0.82
R2Adj.	0.822	0.947	0.839	0.806

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 57. Colorado vs Nebraska (NonMetropolitan Areas): All Data

	Property	Burglary	Larceny Theft	Motor Vehicle Theft
(Intercept)	3911.533***	1024.133***	2670.733***	252.800***
	-299.375	-63.235	-208.033	-20.036
treated	-72.667	-145.4	77.933	36.8
	-423.38	-89.427	-294.203	-28.336
time	-1796.700***	-486.133***	-1298.733***	-47.967
	-560.079	-118.301	-389.194	-37.485
didCO_NE	1110.167	479.733***	525.067	63.367
	-792.071	-167.304	-550.404	-53.011
Num.Obs.	42	42	42	42
R2	0.244	0.308	0.295	0.157
R2Adj.	0.184	0.253	0.24	0.09

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

REFERENCES

Callaway, B., & Sant'Anna, P. H. C. (2021). *BCALLAWAY11/did: Difference in differences with multiple periods*. GitHub. Retrieved February 25, 2022, from https://github.com/bcallaway11/did

Baggio, M., Chong, A., & Kwon, S. (2020). Marijuana and alcohol: Evidence using border analysis and retail sales data. *Canadian Journal of Economics/Revue Canadienne D'économique*, *53*(2), 563–591. https://doi.org/10.1111/caje.12437

Baggio, M., & Chong, A. (2020). Recreational marijuana laws and junk food consumption: Evidence using border analysis and retail sales data. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.3328613

Brinkman, J., & Mok-Lamme, D. (2019). Not in my backyard? Not so fast. The effect of marijuana legalization on neighborhood crime. *Regional Science and Urban Economics*, *78*, 103460. https://doi.org/10.1016/j.regsciurbeco.2019.103460

Burkhardt, J., & Goemans, C. (2019). The short-run effects of marijuana dispensary openings on local crime. *The Annals of Regional Science*, *63*(1), 163–189. https://doi.org/10.1007/s00168-019-00931-0

Davenport, S. (2021, June 28). *How to buy and enjoy cannabis legally in Alaska*. Anchorage Daily News. Retrieved January 26, 2022, from https://www.adn.com/alaska-visitors-guide/2021/06/27/how-to-buy-and-enjoy-cannabis-legally-in-alaska/#:~:text=In%20Alaska%2C%20anyone%2021%20or,from%20out%2Dof%2Dstate.

DISA. (n.d.). *Map of marijuana legality by State*. Retrieved December 13, 2021, from https://disa.com/map-of-marijuana-legality-by-state.

Dragone, D., Prarolo, G., Vanin, P., & Zanella, G. (2017). Crime and the legalization of recreational marijuana. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.2911460

Dube, A., Lester, T. W., & Reich, M. (2010). Minimum wage effects across state borders: Estimates using Contiguous Counties. *Review of Economics and Statistics*, *92*(4), 945–964. https://doi.org/10.1162/rest_a_00039

Federal Bureau of Investigations. (2018, September 10). *UCR Publications*. Retrieved December 13, 2021, from https://www.fbi.gov/services/cjis/ucr/publications.

Freisthler, B., Gaidus, A., Tam, C., Ponicki, W. R., & Gruenewald, P. J. (2017). From medical to recreational marijuana sales: Marijuana Outlets and crime in an era of changing marijuana legislation. *The Journal of Primary Prevention*, *38*(3), 249–263. https://doi.org/10.1007/s10935-017-0472-9

Freisthler, B., Ponicki, W. R., Gaidus, A., & Gruenewald, P. J. (2016). A micro-temporal geospatial analysis of medical marijuana dispensaries and crime in Long Beach, California. *Addiction*, *111*(6), 1027–1035. https://doi.org/10.1111/add.13301

Hao, Z., & Cowan, B. (2017). *The cross-border spillover effects of recreational marijuana legalization* (NBER Working Paper Series No. 23426) [Working paper]. National Bureau of Economic Research. https://doi.org/10.3386/w23426

Holstege, C. P., Butelman, E. R., Kreek, M. J., Pereira, J., & Weigand, T. (2014). *Cannabis Sativa - an overview | ScienceDirect Topics*. Retrieved October 2, 2021, from https://www.sciencedirect.com/topics/agricultural-and-biological-sciences/cannabis-sativa

Huntington-Klein, N. (2022). *The Effect: An Introduction to Research Design and Causality*. CRC Press.

Lee, M. A. (2013). *Smoke signals: A social history of marijuana—Medical, recreational and scientific*. Scribner.

Maier, S. L., Mannes, S., & Koppenhofer, E. L. (2017). The implications of marijuana decriminalization and legalization on crime in the United States. *Contemporary Drug Problems*, *44*(2), 125–146. https://doi.org/10.1177/0091450917708790

Marion, N. E., & Hill, J. B. (2016). *Legalizing marijuana: A shift in policies across America*. Carolina Academic Press.

Sabia, J., Dave, D., Alotaibi, F., & Rees, D. (2021). Is recreational marijuana a gateway to harder drug use and crime? https://doi.org/10.3386/w29038

Siff, S. (2019). *The illegalization of marijuana: A brief history*. Origins. Retrieved April 23, 2022, from https://origins.osu.edu/article/illegalization-marijuana-brief-history?language_content_entity=en

Washington State Liquor and Cannabis Board. (N.D.) *Know the law.* Retrieved January 26, 2022, from https://lcb.wa.gov/mj-education/know-the-law

Weed Seeds USA. (n.d.). *Marijuana Seeds Oregon.* Retrieved January 26, 2022, from https://weed-seeds.com/usa/marijuana-seeds-oregon/

Wu, G., Boateng, F. D., & Lang, X. (2020). The spillover effect of recreational marijuana legalization on crime: Evidence from neighboring states of Colorado and Washington State. *Journal of Drug Issues*, *50*(4), 392–409. https://doi.org/10.1177/0022042620921359