2020

Drug Policy: The Effect of Medical Marijuana on Opioid Consumption During the US Opioid Epidemic

Jonathon David Knudson
The University Of Montana

DRUG POLICY: THE EFFECT OF MEDICAL MARIJUANA ON OPIOID CONSUMPTION DURING THE US OPIOID EPIDEMIC

By

JONATHON DAVID KNUDSON

Bachelor of the Arts in Mathematics, University of Montana, Missoula, MT, 2015

Minor in Economics, University of Montana, Missoula, MT, 2015

Thesis
presented in partial fulfillment of the requirements
for the degree of

Master of the Arts
in Economics

The University of Montana
Missoula, MT

Summer, 2020

Approved by:

Scott Whittenburg, Dean of The Graduate School
Graduate School

Derek Kellenberg, Chair
Economics

Jeff Bookwalter
Economics

Sophia Newcomer
Public and Community Health Sciences

Knudson, Jonathon, M.A., Summer 2020 Economics

US Drug Policy: An Analysis of the United States Opioid Epidemic

Chairperson: Derek Kellenberg

The introduction and subsequent over-prescribing of extended-release opioids in the United States resulted in a large rise in both addiction and overdose. Recognition and regulation of these new drugs as addictive did little to control the supply of opioids to Americans while Prescription Drug Monitoring Programs and Abuse Deterrent reformulations had limited effect to control the problem. Simultaneously, states like Michigan and Rhode Island legalized medical marijuana through voter referenda opening the door for a new approach to pain management. Recent research has found medical marijuana has proven an effective treatment for conditions such as chronic pain and PTSD and could serve as a substitute to extended-release opioids for pain management. Leveraging ARCOS data and controlling for cross-border transaction cost measured as distance to state borders and legal jurisdictions, this study uses a novel identification method and variable set to explore what effect medical marijuana had on opioid use. This analysis finds that medical marijuana is associated with higher opioid use in states that pass such laws and lower use in neighboring states along the shared border. This result highlights both the endogeneity that plagues analysis of addictive substances which likely explains the first result, and the importance of defining new measures to better understand the true nature of the complex decision to use these substances.

Introduction

In the last two decades the United States has undergone a contradicting and unanticipated shift in drug policy. California ratified the first medical marijuana law (MML) in 1996 (Rosalie L. Pacula et al., 2015) and by 2006 ten states had legalized medical marijuana in some fashion. Eight more states had taken similar measures by the end of 2012, with Colorado and Washington decriminalizing marijuana for recreational use. At the same time, the country has been ravaged by an unforeseen epidemic of opioid addiction. Between 1992 and 2012, the number of opioids prescribed in the United States more than doubled from 107.26 million doses to a peak of 277.29 million doses (Newton, 2018). In 2017 the Department of Health and Human Services declared a national emergency to coordinate the effort to end opioid abuse (HHS.gov). In 2017 there were over 47 thousand overdose deaths from opioids (*CDC Injury Center*, 2019). Today, the Department of Health and Human Services (HHS) estimates 130 daily deaths can be linked to the epidemic. Oxycodone and Hydrocodone remain the most abused opioids, and the most prevalent on the street (Cicero et al., 2005).

Both trends have become focal points of research to better understand the nature of addiction and pain management. Lynch and Campbell (2011) compared 18 double-blind, random controlled, medical studies and concluded that marijuana served as an effective treatment for non-cancer chronic pain. While this confirms marijuana's efficacy as a medication, patients need confidence that marijuana will be effective for pain management. Bowles (2012) compared descriptive data available from patient registries and found that 92.2% of patients were prescribed marijuana for the management of chronic pain. Beyond this, Bradford and Bradford (2016) compared Medicare Part D prescribing rates between states, and found that prescriptions for pain dropped 11% in states with medical marijuana. Bradford and Bradford also confirm that opioid prescribing rates drop when medical marijuana is available, confirming patients view marijuana as a substitute to opioids. Finally, Shi (2017) compared hospitalization rates between states and concluded that medical marijuana was associated with a 13% decrease in opioid overdoses. These deaths are highly associated with abusive behavior and have served as a strong indicator of the state of the opioid epidemic.

These studies suggest that marijuana is a substitute for opioids to manage chronic pain and could affect abusive behavior as well. As more states consider implementing medical marijuana programs, or full decriminalization, further research is required to confirm this relationship. Leveraging FDA data measuring the supply of opioids to counties between 2006 and 2012, this study measures what impact medical marijuana laws have on opioid consumption within the state and in neighboring states. To identify the trends between marijuana and opioid consumption, each counties distance to the nearest state border and legal marijuana are used to measure the cost of procurement for each substance. Under a fixed effects analysis, this study finds the demand for opioids decreased by over $1 million in the average county when the distance to the nearest legal marijuana decreases by 100 miles. While endogeneity continues to be the largest issue faced when studying addictive substances, this study confirms that the distance to different legal jurisdictions has an effect on the cost and subsequently the demand for these substances.

Literature Review

The Opioid Epidemic

In 1995, OxyContin was introduced by Purdue Pharma and approved by the FDA for use as a prescription pain reliever (Jones et al., 2018). OxyContin was innovative for its slowed release of oxycodone allowing a single dose to provide relief for up to 12 hours (*FDA Opioid Timeline*, 2019). Before this breakthrough, pain management prescriptions were immediate release which required dosing every 4-6 hours and often caused a euphoric high when taken. Purdue Pharma marketed OxyContin as non-addictive because the extended-release mechanism prevented the initial spike in euphoria from normal consumption (Jones et al., 2018). The unseen danger laid in abuse of opioid prescriptions, which sabotaged the time delay feature of OxyContin to receive the full dose of oxycodone at once. Purdue Pharma pled guilty in 2007 to misleading patients, medical providers, and government officials by claiming that OxyContin was non-addictive (Meier, 2007). By this time, the damage had been done and a massive shift in pain management had occurred in the United States.

It is worth clarifying nomenclature for this study. For simplicity, take opioids to represent all medications that contain opium-derived substances including hydrocodone, oxycodone, and synthetic opioids such as fentanyl. To achieve euphoric high, these medications can be used in ways unintended by medical professionals. Collectively referred to as abuse, this includes taking much higher doses than prescribed or crushing extended-release pills (such as Oxycontin) for an increased immediate effect. More recently, synthetic opioids such as fentanyl have been prescribed as a dermal patch intended to slowly release the medication while the patch is worn. Wearing multiple patches at once or extracting the medication from the patch and injecting the raw opiate are common forms of abuse (US GAO, 2011).

In addition to how medications are abused, a vital question is how they are obtained. Most opioids are obtained through diversion, the act of removing medications from legitimate supply chains for illegitimate use. Some forms of diversion include outright theft from pharmacies or forgery of prescriptions. One pharmacist in Pennsylvania made over $900,000 illegally selling prescriptions through the back of his store, which he lost in the stock market before being caught (Offit, 2017). The vast majority of illegal opioids are diverted through “doctor shopping” where patients visit numerous medical providers to get as many prescriptions as possible (Newton, 2018). The Government Accountability Office (GAO) completed a review of prescriptions filled by Medicare Part D beneficiaries and identified patients by the number of opioid doses they received and the number of physicians writing the prescriptions. Doctor shopping was suspected when patients received more doses than would be reasonably needed in a year. The GAO found that 71% of suspected doctor shoppers received prescriptions from more than 5 providers in one year (US GAO, 2011). The same authors found that 80% of suspected doctor shoppers sought prescriptions for OxyContin or hydrocodone and noted one patient that received prescriptions from 87 unique medical providers in one year. Extended release medications fueled opioid addiction by providing higher doses of oxycodone and hydrocodone in a single pill, and became the focus of policy makers for more than a decade to curtail the ensuing addiction.

Abuse-Deterrent Reformulation

In 2010, abuse-deterrent (non-crushable) formulas were approved by the FDA. These changes made crushing the tablets much more difficult to prevent further abusive behaviors. Using a time series analysis of opioid prescribing rates, Alpert et al. (2018) found that non-medical abuse of opioids reduced by up to 40% but subsequently resulted in large increases in use of heroin and other illegal substances available for substitution. Because random trials were not used in this analysis, Alpert et al. note their results imply causality rather than confirming it. Cicero and Ellis (2015) reached the same conclusion after conducting interviews with a group of individuals who self-identify with an opioid addiction; respondents were questioned about potentially abusive behaviors before and after the reformulation. Of those respondents that quit these methods of OxyContin misuse, 70% reported substituting to heroin due to the change.

Both Alpert et al. and Cicero and Ellis identify a danger of supply-side intervention in the drug market, which often drives demand through substitution to other addictive substances. Cicero et al. (2005) note that opioids are easier to obtain in rural and suburban areas than heroin, and individuals with addiction are less likely to be caught by law enforcement using opioids than street drugs. If these individuals are driven to substitute, their risk of overdose increases because street drugs have inconsistent dosing and purity where prescriptions have government-regulated standards to control for such concerns (Cicero et al., 2005).

Prescription Drug Monitoring Programs

To combat doctor shopping, policymakers began implementing Prescription Drug Monitoring Programs (PDMP) to enable providers and prevent overprescribing

(Buchmueller & Carey, 2018). At the beginning of the crisis, patients would "shop" doctors in a close area, limiting travel to use different pharmacies and providers. In the early years of the opioid epidemic, there were few PMPD's and all were contained to their respective state borders (Bulloch, 2018). The majority (70%) of existing PMPD's were founded between 2000 and 2015. In the initial years, doctors were asked to voluntarily report patients suspected of opioid diversion or misuse (Bulloch, 2018). Buchmueller and Carey (2018) find that voluntary programs do not affect doctor shopping.

The PDMP Center of Excellence (2014) recommends states mandate doctor reporting and program usage for all scheduled drug prescriptions. Using time series analysis of prescribing rates, Buchmueller and Carey (2018) find that when states make this change, all opioid prescribing rates decrease. Despite this, Buchmueller and Carey also conclude that mandatory PDMPs drive demand across state borders to continue doctor shopping. Presently, 49 states and the District of Columbia have enacted PDMPs and 46 states participate in a national collaboration with the PMP Interconnect (*PDMP FAQ*). Despite these extensive efforts, some medical professionals continue to enable illegal efforts for various reasons. In Virginia, a doctor was sentenced to 40 years in prison after he prescribed 500 thousand opioid doses in 2 years, resulting in 861 federal drug convictions (Hassan, 2019).

Economic Theory and Marijuana

To model changes in drug policy, economists have turned to the "shadow cost" of consumption (Bretteville-Jensen & Biørn, 2004; Saffer & Chaloupka, 1999; van Ours, 1995). The shadow cost for an illicit good includes the inherent cost of purchase, the risks of illegal activity (arrest, reputation, and other legal ramifications), transaction costs to obtain the illicit substance, and issues with drug quality. Prescription drug monitoring programs increase opioid shadow costs by increasing the transaction cost of diversion (Buchmueller & Carey, 2018). Medical marijuana programs decrease shadow costs by providing legal and social amnesty to patients and set legal standards for product testing and purity (Bowmaker, 2005). Early research into marijuana focused on its effect on mental health, employment outcomes, and educational attainment. Van Ours and Williams (2015) completed a broad survey of prior econometric research to consider what affects marijuana may have similar to drug use. While marijuana use is strongly associated with increased rates of depression and anxiety, Van Ours and Williams find that most studies fail to rule out reverse causality and underlying endogeneity. Despite this, Van Ours and Williams conclude employment status and wages are not affected by marijuana use.

Sabia and Nguyen (2018) expand this by investigating the effect of medical marijuana law (MML) on wages and employment in a state level analysis of the United States. Sabia and Nguyen found medical marijuana had no effect on these measures. Even though this recognition significantly reduces some aspects of the shadow cost of marijuana, the effect of the policy is limited by the transaction costs to purchase marijuana. When states legally recognize medical marijuana dispensaries, these transaction costs decrease and access to marijuana increases (Rosalie L. Pacula et al., 2015). Brinkman and Mok-Lamme (2017) use a novel approach by measuring crime in a "highly localized" dataset. These measures are then matched with indicator variables for whether a recreational dispensary opened in the neighborhoods observed. Controlling for geospatial effects, Brinkman and Mok-Lamme find a sharp decline in crime when dispensaries open locally. Dragone et al. (2018) reach the same conclusion after completing a county level analysis of the border between Oregon and Washington. With legalized recreational marijuana available in Washington, there was a decrease in crime both in state and across the border. In particular, this effect was measured using a spatial regression discontinuity design.

To understand if a similar effect occurred in the opioid epidemic, Shi (2017) used hospitalization records from 1997 through 2014 and found MMLs which recognize dispensaries are associated with a 23% decrease in admittance related to opioid addiction, and an 11% decrease in admittance from opioid overdose. Powell et al. (2018) reach the same conclusion using different data to measure opioid related hospitalization rates. Each researcher noted the importance of medical dispensaries as a measure of access to medical marijuana product, lowering transaction costs.

Data

ARCOS Prescription Data

Table 1. Transactions used to tabulate dataset by Year

Year	Transaction Count
2006	1,415,038
2007	1,596,945
2008	1,738,569
2009	1,790,102
2010	1,999,285
2011	2,087,355
2012	2,147,903
Total	12,775,197

Pursuant to a Freedom of Information Act request filed by the Washington Post (2019), the DEA released data from the Automation of Reports and Consolidated Orders System (ARCOS) detailing the supply of opioids between the years of 2006 and 2012, which was later expanded to 2014. This database records every supply chain transaction for all federally controlled substances until dispensed to the patient. In addition to all relevant details of the buyer and seller this database tracks the drug name, number of doses, strength of the dose, and the amount of the "base" drug purchased (i.e. hydrocodone or oxycodone). Sellers are required to report these transactions for all controlled substances based on federal law. Based on the time frame of this study, Medical Marijuana Laws (MML) enacted in Michigan and Rhode Island are the focus of this research. Both states underwent marijuana decriminalization (removing legal penalties for patients) during this period.

Table 2. Count of transactions used to tabulate dataset for selected states.

State	Medical Marijuana Decriminalization	Transactions in Data
Connecticut		1,096,271
Indiana		2,185,607
Massachusetts		1,567,857
Michigan	Dec 2008	2,610,515
Ohio		3,120,430
Rhode Island	Jan 2008	360,905
Wisconsin		1,833,612
Total		**12,775,197**

The number of observations in each state and year are provided in Tables 1 and 2 respectively.[1] There is a steady increase in the number of transactions between 2006 and 2014. The states with medical marijuana laws enacted during this time frame have been highlighted in green in Table 2. Pharmacies are discouraged by regulators and insurance companies from holding large quantities for fear of break in, theft, or diversion by

[1] Two transactions were excluded from this analysis as outliers caused by reporting error. Each transaction represented an unprecedented order for pharmacies that typically order small amounts.

employees (Newton, 2018). The same authors note federal law restricts the quantity of opioids that can be dispensed to a patient at one time, limiting supplies for chronic pain to one month. By summing orders for each month, the total grams of hydrocodone and oxycodone sold to pharmacies proxies the demand for each drug in that month. Similarly, summing the total pill count delivered in each month gives a proxy for the demand for opioid doses in each county. Finally, the combined effect of these drugs can be observed by multiplying the weight of each drug by the morphine equivalence factor to reach the equivalent weight of morphine and then summing these weights for each county and month. Together, these measures represent a time-series panel dataset to on opioid use from 2006 through 2012.

Table 3. Summary statistics for all states

Variable	Mean	St Dev	Min	Max
Hydrocodone (Kilograms)	1,616.7	7,752.4	0	1,043,302
Connecticut	1,202.4	1,349.2	77.6	16,134.5
Indiana	1,635.8	12,311.2	0	1,043,302
Massachusetts	2,270.9	4,789.0	1.9	41,588.2
Michigan	2,248.6	7,286.0	7.4	91,133.3
Ohio	1,835.0	5,622.5	0.0	161,716.3
Rhode Island	2,015.3	2,139.3	68.0	11,670.7
Wisconsin	465.4	1,310.0	1.9	38,388.8
Oxycodone (Kilograms)	1,449.1	4,438.7	0	89,866.6
Connecticut	6,063.2	7,093.1	391.5	31,134.0
Indiana	437.5	1,331.3	0	70,263.8
Massachusetts	7,091.1	6,590.5	24.9	44,644.8
Michigan	662.7	2,921.0	0.2	58,617.0
Ohio	2,411.9	6,120.7	8.2	89,866.6
Rhode Island	1,969.0	2,194.5	136.6	10,524.1
Wisconsin	777.8	3,748.7	0.2	56,524.7
Hydrocodone (Pills)	143,641.5	316,345	0	3,095,200
Connecticut	358,334.9	251,794.3	45,900	926,270
Indiana	220,044.9	366,075.7	0	3,845,270
Massachusetts	359,266.8	306,173.9	1,600	1,115,744
Michigan	355,735.3	870,265.9	3,860	8,888,605
Ohio	257,534.5	410,964.2	200	3,055,060
Rhode Island	355,819.2	360,680.3	19,500	1,307,170
Wisconsin	120,786.5	21,4906	1,800	1,942,771
Oxycodone (Pills)	251,388.1	521,542.9	0	8,888,605
Connecticut	646,651.9	553,666.1	86,900	2,064,214
Indiana	58,647.3	117,782.6	0	1,544,780
Massachusetts	730,241.5	523,107.7	8,600	1,944,800
Michigan	58,402.0	139,403.0	100	1,605,680
Ohio	202,148.9	377,417.6	2,300	3,095,200
Rhode Island	251,524.0	244,896.2	29,200	995,900
Wisconsin	97,573.8	273,507.5	100	3,048,220

Table 4. Summary statistics for all states.

Variable	Mean	St Dev	Min	Max
Hydrocodone (Grams per capita)	13.03	28.81	0	3,778.74
Connecticut	2.80	2.53	0.52	59.57
Indiana	21.72	47.56	0	3,778.74
Massachusetts	3.89	6.29	0.19	56.23
Michigan	15.52	24.04	0.69	819.55
Ohio	11.13	17.30	0.00	439.41
Rhode Island	8.71	5.75	1.15	40.05
Wisconsin	4.54	5.86	0.12	217.15
Oxycodone (Grams per capita)	7.64	19.76	0	1,236.53
Connecticut	11.36	6.31	2.62	36.16
Indiana	6.11	15.90	0	1,236.53
Massachusetts	15.47	8.27	2.47	83.80
Michigan	3.05	3.52	0.01	82.27
Ohio	14.32	34.57	0.32	1,042.33
Rhode Island	8.44	3.77	2.69	23.40
Wisconsin	4.56	4.91	0.01	62.09
Hydrocodone (Pills per capita)	2.31	1.36	0	14.94
Connecticut	0.89	0.23	0.30	1.59
Indiana	3.14	1.47	0	10.44
Massachusetts	0.77	0.25	0.16	1.50
Michigan	2.99	1.37	0.38	14.94
Ohio	1.95	0.84	0.01	7.14
Rhode Island	1.56	0.55	0.38	3.04
Wisconsin	1.42	0.59	0.10	4.02
Oxycodone (Pills per capita)	0.95	0.62	0	8.75
Connecticut	1.42	0.34	0.58	2.39
Indiana	0.80	0.50	0	4.27
Massachusetts	1.74	0.45	0.82	3.41
Michigan	0.51	0.30	0.01	2.36
Ohio	1.38	0.72	0.10	8.75
Rhode Island	1.19	0.34	0.57	2.39
Wisconsin	0.88	0.44	0.00	3.22

Table 5. Summary statistics for all states and years.

Variable	Mean	St Dev	Min	Med	Max
Morphine Equivalence (Kilograms)	3,790.40	11,824.5	0.03	875.85	1,045,560
2006	2,682.77	6,858.27	0.03	597.28	97,283.5
2007	3,198.45	8,729.80	5.23	715.41	109,456.0
2008	3,415.60	10,107.99	5.06	791.85	168,802.2
2009	3,920.09	10,457.50	5.97	965.99	156,825.1
2010	4,000.70	10,333.91	3.00	946.34	122,240.2
2011	4,456.74	11,532.03	4.16	1,056.97	184,760.0
2012	4,859.11	20,020.43	4.76	1,115.23	1,045,560
Connecticut	10,297.30	11,665.4	754.95	4,082.94	48,773.08
Indiana	2,292.15	12,800.23	0.03	864.81	1,045,560
Massachusetts	12,907.64	13,715.96	44.73	11,575.53	108,555.46
Michigan	3,242.72	11,163.85	9.90	617.90	144,437.83
Ohio	5,452.97	13,356.40	17.92	1,357.15	188,313.19
Rhode Island	4,968.91	5,190.50	332.48	2,440.64	20,855.83
Wisconsin	1,632.24	6,631.27	3.00	330.23	93,269.40
Morphine Equivalence (Grams per capita)	24.50	43.53	0.00	16.62	14.94
2006	19.42	51.51	0.00	11.33	1,599.42
2007	21.34	53.54	0.31	13.53	1,658.12
2008	20.64	21.24	0.33	14.93	327.07
2009	25.84	27.00	0.40	17.88	395.53
2010	25.13	24.01	0.20	18.30	298.96
2011	28.19	29.32	0.28	21.01	617.11
2012	30.96	70.83	0.32	22.11	3,786.92
Connecticut	19.86	10.24	5.07	17.62	66.84
Indiana	30.90	54.89	0.00	22.51	3,786.92
Massachusetts	27.10	16.63	4.41	24.18	146.79
Michigan	20.11	25.70	1.07	14.64	820.66
Ohio	32.62	59.74	1.02	21.50	1,658.12
Rhode Island	21.39	10.23	5.94	19.01	58.44
Wisconsin	11.39	10.46	0.20	8.84	223.88

Measures of Distance and Medical Marijuana Law

With the implementation of PDMPs, doctor shopping has evolved to circumvent these restrictions. Individuals with addiction or who divert opioids travel necessary distances to see multiple providers and receive as many prescriptions as possible. Presumably, these individuals travel the shortest distance possible across monitoring borders. In the same vein, medical marijuana would be more accessible to patients outside of the intended state as a function of the distance to that state's border. The National Bureau of Economic Research (NBER) provides a dataset which provides the distance between all counties in the United States. For each county in this study, the distance to the nearest border is measured as the shortest distance to a county in a different state. The distance to the nearest medical marijuana is measured as the shortest distance to either Michigan or Rhode Island. Because medical marijuana is only legal for a portion of the study period, this distance is set to 500 miles for all counties prior to legalization and is set to 1 mile for counties inside Michigan and Rhode Island. The first is an arbitrary measure chosen to cap the potential distance a person would be willing to travel to purchase marijuana in a jurisdiction where it is legal; traveling farther than this would be unexpected when compared to the relative cost of black-market activity. The second is to prevent the loss of observations if a log specification is used and would represent the last mile cost of visiting a commercial store.

To properly measure the impact of medical marijuana, this study focuses on when these laws are effective for patients (versus when the laws were enacted). Each state determined how to define their MML, and as a result no two states have the same laws.

Early MMLs focused on how legal amnesty was granted to patients and medical providers, and patients were often limited to cultivating their own marijuana at home. To know when each law was effective for patients, it is necessary to review the history of medical marijuana in each state.

Michigan has a unique history with medical marijuana. The initial MML passed was vague and did not clarify if dispensaries were legal (Associated Press, 2011; Rosalie L. Pacula et al., 2015). Dispensaries in the state operated under this legal vagueness from November 2008 through February 2013 when the Michigan Supreme Court ruled the initial law did not grant amnesty to dispensaries (The Huffington Post, 2013). This is corroborated with multiple reports of sporadic law enforcement raids of these dispensaries during this time (Associated Press, 2011). This means Michigan effectively had medical dispensaries during this time, even though the law did not allow for them.

In comparison to this, Rhode Island followed a traditional timeline in legalizing medical marijuana. The state's first medical marijuana law gave patients protection with optional registration with the state in 2008 (Rosalie Liccardo Pacula et al., 2014). In 2010, registration became mandatory but gave additional protections to patients by preventing law enforcement from issuing citations. Pacula et al. (2014) note the importance of both making registration optional and providing additional legal protections to patients, but both policies give similar outcomes. To combine this information with the measures for opioid use, marijuana legality is coded as a 1 for all observations after December 2008 in Michigan and after January 2008 in Rhode Island. All other observations are coded as a 0.

Control Variables

To control for endogenous differences between counties, control variables were aligned with the above data sources from the American Community Survey conducted by the US Census Bureau. This survey is conducted through the course of each year and is used to estimate a variety of community and population measures between the decenial censuses. Population measures include the total county population, the proportion of the population that is female, median household income, and the proportion of the population living in poverty. Additionally, the proportion of each of the Black, American Indian, Asian, and Pacific Islander communities are included. Finally, the population is broken down by proportion in age brackets for those 19 years and under, 20 to 39 years in age, 40 to 64 years in age and above 65 years in age. These data points are provided on an annual basis for each county and are combined on a county to county basis with the aggregated ARCOS data, categorical MML data, and distance measures with each year paired with every pre-existing datapoint in that year.

Model

To estimate the affect these policy shifts have on the demand for opioids, it is necessary to use a fixed effects time series regression at the county level. Fixed effects are included to control for invariant endogeneity between states and over time, allowing the model to capture the difference between like observations and between periods. For each measure of opioid demand, I estimate the linear form:

$$y_{c,m,i} = \alpha_m + \gamma_s + \beta_1 MML_{s,m} + \beta_2 (Border\ Distance)_c + \beta_3 (Marijuana\ Distance)_m + \chi_{c,y} + \epsilon_{c,m} \quad (1)$$

where $y_{c,m,i}$ represents each of the five measures to proxy opioid demand: grams oxycodone, grams hydrocodone, grams morphine equivalence, oxycodone pill count, and hydrocodone pill count. The subscript m indicates variables measured by month while y indicates variables measured by year. Similarly, s represents variables measured at the state level while c represents variables measured at the county level. As noted by Van Ours and Williams (2015), heterogeneity remains a large issue when estimating the effects of marijuana consumption. By controlling for monthly and state fixed effects that may affect opioid demand over time or within states, time and county invariant heterogeneity between observations is minimized. This model assumes these unobserved effects are uncorrelated with the error of the estimation. The vector $\chi_{c,y}$ represents annual control variables including population, unemployment, and income for each county. This model must meet the assumption that the explanatory variables are not associated with the error of the model. Similarly, testing will be required to confirm the error term is not heteroskedastic.

This model captures the effect of medical marijuana in the coefficient for the MML variable. $MML_{s,m}$ is an indicator variable tracking whether medical marijuana patients are granted legal amnesty. If this model finds results consistent with Shi (2017), then β_1 will be negative confirming that medical marijuana laws reduce overall opioid consumption. $Border\ Distance_c$ is measured for each county and represents the shortest direct distance to a county outside of the state. A negative value for β_2 is consistent with opioid diversion through doctor shopping across state borders. This would represent an increase in cost with further travel distance resulting in lower demand for opioids. $(Marijuana\ Distance)_m$ is measured by county and represents the shortest distance to a county with legal amnesty for medical marijuana patients. Should marijuana serve as a substitute for opioid consumption, β_3 will be positive. This would confirm that opioid consumption declines as the cost of traveling for medical marijuana is reduced. Because control variables (including population, unemployment, and income) can only be found on an annual level, errors are clustered at the county level. Because of the increase in the number of transactions each year noted in Table 1, the model may have issues with heteroskedasticity. Pharmacies may be ordering more in general or may have started ordering smaller amounts more frequently. Either issue has potential for causing time dependent changes in the variance of the model's error term. If this does happen, this can be resolved using robust standard errors in combination with clustered errors (Cameron & Miller, 2015).

Results

The regression estimates of equation (1) are shown in Table 6. The effect on the total weight of opioids delivered to counties is detailed in column 1 while the effect on the demand for doses is detailed in column 4. The effects for each drug (oxycodone and hydrocodone) are then broken down in the subsequent columns for both weight and doses. Medical Marijuana Law (MML)[2] is associated with a 7.27% increase in combined opioid weight (by morphine equivalence per capita) and a 4.70% increase in combined pill count per capita delivered to counties, relative to counties without medical marijuana laws. This effect is lower for Oxycontin, where MML is associated with an 11.57% decrease in grams per capita delivered and a 2.82% increase in pill count per capita, all else constant. Comparatively, MML have a much stronger effect on Hydrocodone delivered, and are associated with a 15.14% increase in the grams per capita and a 6.92% increase in pills per capita delivered to counties, all else constant. The estimates for hydrocodone are significant with p-values less than 0.01, while the remaining estimates have mixed significance.

A one standard deviation (35.4 mile) decrease in the distance to the nearest border county is associated with a 3.54% decrease in the total grams per capita (morphine equivalence) and a 3.25% decrease in the pill count per capita, all else constant. This effect is consistent between all models, measuring a 1.9-5.1% decrease in the demand for opioids in counties closer to their state borders, and does not hold statistical significance.

---

[2] All interpretations for MML are reached using the interpretation for an indicator variable regressed against a logged variable: $(e^{bx} - 1) * 100$ % Effect.

Table 6. Regression results from the model proposed. Note the base case for State is Connecticut, the base case for age cohorts are adults 65 and older, and the base case for race is Caucasian.

VARIABLES	(1) Morphine Equiv.	(2) Grams Oxy	(3) Grams Hydro	(4) Total Pill Count	(5) Oxy Pill Count	(6) Hydro Pill Count
Percent of Population Female	8.014***	9.915***	5.980**	4.593**	5.268**	4.177**
	(2.854)	(3.618)	(2.755)	(1.979)	(2.581)	(1.914)
Log: Median Household Income	-0.317	-0.0976	-0.666	-0.395	-0.150	-0.537*
	(0.428)	(0.458)	(0.459)	(0.275)	(0.310)	(0.283)
Log: Population (Annual)	0.414***	0.435***	0.429***	0.220***	0.230***	0.230***
	(0.0585)	(0.0694)	(0.0549)	(0.0358)	(0.0454)	(0.0341)
Black Population (Percent)	-2.614***	-2.998**	-3.130***	-2.164***	-2.533***	-2.470***
	(0.891)	(1.178)	(0.887)	(0.489)	(0.700)	(0.493)
American Indian Population (Percent)	-1.425***	0.0820	-0.544	-0.235	1.194***	0.182
	(0.507)	(0.590)	(0.448)	(0.334)	(0.372)	(0.321)
Asian Population (Percent)	-8.242**	-6.735	-8.711***	-6.526***	-5.883**	-5.754***
	(3.436)	(4.118)	(3.293)	(1.969)	(2.533)	(1.898)
Pacific Islander Population (Percent)	15.84	17.05	50.03	9.616	38.34	5.820
	(68.02)	(85.66)	(75.11)	(41.68)	(57.33)	(41.34)
All in Poverty (Percent)	0.0644***	0.0656***	0.0488***	0.0320***	0.0307***	0.0297***
	(0.0147)	(0.0178)	(0.0154)	(0.00915)	(0.0114)	(0.00929)
Population 0 to 19 years (Percent)	-3.237	-3.157	-2.671	-2.903**	-3.439**	-2.689*
	(2.132)	(2.423)	(2.193)	(1.366)	(1.540)	(1.420)
Population 20 to 39 years (Percent)	6.804***	9.365***	4.858**	3.835***	5.425***	2.976**
	(2.080)	(2.281)	(2.189)	(1.398)	(1.544)	(1.438)
Population 40 to 64 years (Percent)	13.21***	16.77***	10.35***	6.682***	8.598***	5.973**
	(3.696)	(4.071)	(3.507)	(2.504)	(2.864)	(2.495)
Medical Marijuana Legal Binary	0.0702	-0.123**	0.141***	0.0459**	0.0278	0.0669***
	(0.0498)	(0.0537)	(0.0509)	(0.0208)	(0.0307)	(0.0210)
Distance: Nearest County Out of State (100 Miles)	0.0999	0.145	0.0536	0.0917	0.0780	0.0667
	(0.101)	(0.118)	(0.107)	(0.0646)	(0.0788)	(0.0662)
Distance: Nearest Medical Marijuana (100 Miles)	0.0396***	0.0452***	0.0228**	0.0263***	0.0196***	0.0281***
	(0.0112)	(0.0127)	(0.0108)	(0.00630)	(0.00723)	(0.00643)
Date	0.00706***	0.00896***	0.00569***	0.00636***	0.00771***	0.00582***
	(0.00130)	(0.00147)	(0.00133)	(0.000771)	(0.000891)	(0.000784)
Month Fixed Effects						
Month: February	-0.0249***	-0.0505***	-0.0121	-0.0371***	-0.0608***	-0.0276***
	(0.00830)	(0.00964)	(0.0100)	(0.00434)	(0.00545)	(0.00512)
Month: March	0.0903***	0.0770***	0.0978***	0.0736***	0.0688***	0.0745***

	(0.00883)	(0.00966)	(0.0105)	(0.00457)	(0.00546)	(0.00566)
Month: April	0.0169*	-0.0279***	0.0627***	0.0310***	-0.00376	0.0498***
	(0.00963)	(0.00965)	(0.0110)	(0.00524)	(0.00576)	(0.00577)
Month: May	0.0745***	0.00496	0.131***	0.0743***	0.0314***	0.0935***
	(0.0100)	(0.00924)	(0.0114)	(0.00582)	(0.00592)	(0.00630)
Month: June	0.124***	0.0512***	0.178***	0.0962***	0.0578***	0.114***
	(0.0113)	(0.0104)	(0.0129)	(0.00617)	(0.00604)	(0.00690)
Month: July	0.0943***	0.0393***	0.141***	0.0780***	0.0448***	0.0961***
	(0.0117)	(0.0112)	(0.0134)	(0.00648)	(0.00679)	(0.00727)
Month: August	0.121***	0.0432***	0.181***	0.102***	0.0602***	0.124***
	(0.0127)	(0.0125)	(0.0146)	(0.00710)	(0.00758)	(0.00792)
Month: September	0.0931***	0.0117	0.140***	0.0496***	0.0142*	0.0642***
	(0.0141)	(0.0134)	(0.0157)	(0.00759)	(0.00819)	(0.00814)
Month: October	0.116***	0.0320**	0.179***	0.0860***	0.0459***	0.105***
	(0.0146)	(0.0141)	(0.0165)	(0.00814)	(0.00877)	(0.00902)
Month: November	0.0647***	0.00227	0.109***	0.0392***	0.0183*	0.0503***
	(0.0153)	(0.0157)	(0.0164)	(0.00865)	(0.00968)	(0.00920)
Month: December	0.175***	0.0970***	0.225***	0.115***	0.0717***	0.134***
	(0.0140)	(0.0142)	(0.0155)	(0.00840)	(0.00921)	(0.00904)
State Fixed Effects						
State: IN	0.673***	-0.307	2.164***	0.537***	-0.419***	1.228***
	(0.168)	(0.191)	(0.182)	(0.0982)	(0.114)	(0.111)
State: MA	0.0954	0.123	-0.172	-0.0660	0.0691	-0.314***
	(0.136)	(0.148)	(0.202)	(0.0724)	(0.0898)	(0.0956)
State: MI	-0.0965	-1.206***	1.446***	0.191*	-1.102***	0.940***
	(0.168)	(0.191)	(0.186)	(0.0992)	(0.115)	(0.114)
State: OH	0.303*	0.114	1.192***	0.213**	-0.0123	0.606***
	(0.167)	(0.182)	(0.183)	(0.0908)	(0.105)	(0.106)
State: RI	0.0333	-0.133	0.962***	0.0378	-0.271***	0.398***
	(0.157)	(0.157)	(0.194)	(0.0872)	(0.0950)	(0.108)
State: WI	-0.347**	-0.575***	0.578***	-0.0408	-0.393***	0.403***
	(0.156)	(0.172)	(0.166)	(0.0861)	(0.105)	(0.0983)
Constant	-13.03***	-20.34***	-7.951*	-6.373**	-11.75***	-4.927*
	(4.075)	(4.373)	(4.244)	(2.689)	(3.058)	(2.692)
Observations	30,216	30,216	30,216	30,216	30,216	30,216
R-squared	0.442	0.467	0.516	0.435	0.514	0.575

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

A similar effect is observed in states without MMLs; a 100-mile decrease in the distance to the nearest border with medical marijuana is associated with a 3.96% decrease in grams per capita (morphine equivalence) and a 2.63% decrease in the pill count per capita, all else constant. This effect is consistent between 1.9% and 4.5% and all estimates are significant with p-values less than 0.01.

A one percent increase in median household income is associated with a 0.317% decrease in the total grams per capita (morphine equivalence) and a 0.395% decrease in the total pill count per capita, all else constant. At the average of observed annual income ($\bar{x} = \$46{,}614$) a $1,000 increase in median household income is associated with 0.166 gram per capita decrease in total morphine equivalence and a 0.028 pill per capita decrease in pills per capita delivered to counties each month. For comparison, counties received 24.37 grams per capita (morphine equivalence) and 3.252 pills per capita on average each month. These estimates don't hold strong significance. The coefficients for population show that larger populations are associated with larger per capita opioid measures. The estimates show a ten thousand person increase in population is associated with a 0.03% increase in the dependent weight measures and a 0.021% increase in the pill count per capita delivered to counties in a month.

The model estimates consistent effects for all dependent measures of opioid supply with regard to age; older populations are associated with higher measures of opioids both by weight and number of doses, relative to adults over the age of 65. Consistently, a one percent increase in the population under 20 is associated with a 3% decrease in all dependent measures, all else constant. A one percent increase in the population ages 20 to 39 is associated with a 4-7% increase in all opioid measures, all else constant. The largest effect is estimated for the population ages 40 to 64; a one percent increase in this population is associated with a 10-16% increase in grams of opioids delivered to counties, and a 6-8% increase in doses delivered to counties in a month, all else constant. For the latter two groups, these estimates are all significant, and larger effects are estimated for oxycodone specifically. These results are similar to those found by Alpert et al. (2018), who investigated the effect of abuse-deterrent reformulation on the opioid overdose deaths. Alpert measured the largest effect in the age group 25 to 64 years old, followed by the effect measured for the group 0 to 24 years old. The effect measured for the group 65 years or older was insignificant and small. These effects indicate higher overdose rates in these cohorts following the introduction of abuse-deterrent reformulations. Because higher overdose rates indicate increased access to opioids, the differences between these estimates and those found through this paper's model are likely attributed to the difference in age cohort specification.

The model also makes consistent estimates for the effects of the other control variables on the supply of opioids to counties. A one percent increase in the female population is associated with an 8% increase in the weight of opioids supplied and a 4.6% increase in the doses supplied, all else constant. Murphy et al. (2015) also find that the proportion of the population that is female is associated with increased likelihood to abuse opioids, but Kelly (2019) finds that larger female populations are associated with lower overdose deaths. This confirms the endogeneity between addiction and risk of overdose which may affect estimates. Finally, one percent increase in the black population is associated with a 2.6% decrease in all measures of opioids supplied to counties in a month, all else constant. This estimate is consistent with Kelly (2019), who found overdose deaths decrease as the black population increases.

A review of the residuals for this model largely shows random scatter as expected but indicates a strong concern that serial correlation is affecting the models estimates. This is likely the effect of endogeneity common to studies of addictive substances noted by Van Ours and Williams (2015). Alternative specifications including a lagged variable model are considered to establish the robustness of these estimates.

Robustness Testing

Four models are considered and provided in Tables 7 and 8 which both have the results of the original model in the first column. Model (2) considers an alternative specification to measure the potential effect medical marijuana law may have on doctor shopping. Counties are identified with one indicator variable if they are on the border of their respective state, while another category of counties are identified if they directly border a state that has ratified a medical marijuana law. This estimate is similar to the original model; counties on the border of their state are associated with a 11.66% decrease in total grams per capita (morphine equivalence) and an 8.73% decrease in total doses per capita, relative to non-border counties and all else constant. Counties that border a state with medical marijuana are associated with a 21.73% decrease in the total grams per capita (morphine equivalence) and an 7.06% decrease in total doses per capita. This is consistent with the original model which estimates higher opioid consumption in counties farther from the state border. In this model medical marijuana laws are associated with a 3.73% decrease in the total grams per capita (morphine equivalence)

Table 7. Regression of Total Morphine Equivalence per Capita (in grams) on various specifications. Fixed effects are notes but not shown.

VARIABLES	(1) Original Model	(2) Border Binaries	(3) Lagged Variable	(4) Trend	(5) Alternative Age Specification
Female Population (Percent)	8.014*** (2.854)	7.542*** (2.870)	1.160*** (0.411)	8.039*** (2.855)	8.051*** (2.885)
Log: Median Household Income	-0.317 (0.428)	-0.325 (0.431)	-0.0273 (0.0638)	-0.398 (0.420)	0.329 (0.396)
Log: Annual Population (Count)	0.414*** (0.0585)	0.424*** (0.0587)	0.0605*** (0.00981)	0.415*** (0.0584)	
Black Population (Percent)	-2.614*** (0.891)	-2.699*** (0.889)	-0.389*** (0.135)	-2.581*** (0.890)	-2.830*** (0.905)
American Indian Population (Percent)	-1.425*** (0.507)	-1.449*** (0.511)	-0.218*** (0.0696)	-1.411*** (0.507)	-1.335*** (0.470)
Asian Population (Percent)	-8.242** (3.436)	-8.451** (3.455)	-1.343*** (0.506)	-8.153** (3.426)	-10.93*** (3.270)
Pacific Islander Population (Percent)	15.84 (68.02)	15.05 (69.71)	5.727 (10.18)	12.74 (67.59)	17.82 (65.84)
All in Poverty (Percent)	0.0644*** (0.0147)	0.0651*** (0.0148)	0.00948*** (0.00228)	0.0615*** (0.0145)	0.0726*** (0.0154)
Population 0 to 19 years (Percent)	-3.237 (2.132)	-3.612* (2.096)	-0.527 (0.322)	-3.030 (2.116)	
Population 20 to 39 years (Percent)	6.804*** (2.080)	6.321*** (2.112)	0.964*** (0.328)	6.974*** (2.074)	
Population 40 to 64 years (Percent)	13.21*** (3.696)	12.56*** (3.690)	1.842*** (0.611)	13.41*** (3.688)	
Medical Marijuana Legal	0.0702 (0.0498)	-0.0388 (0.0421)	0.0281*** (0.00715)	0.0756 (0.0495)	0.0527 (0.0501)
Year	0.0847*** (0.0156)	0.0578*** (0.0130)	0.00389* (0.00234)		0.0657*** (0.0156)
Distance: Nearest County Out of State (100 Miles)	0.0999 (0.101)		0.0160 (0. 0148)	0.103 (0.101)	0.0517 (0.105)
Distance: Nearest Medical Marijuana (100 Miles)	0.0396*** (0.0112)		0.00303* (0.00169)	0.0446*** (0.0107)	0.0324*** (0.0110)

Border Counties		-0.124* (0.0694)			
Counties that border Marijuana Policy		-0.245 (0.150)			
Log: Lagged Morphine Equiv. (g per cap)			0.852*** (0.0125)		
Date				0.00782*** (0.00122)	
Log: Population 0 to 19 years (Count)					-2.233*** (0.418)
Log: Population 20 to 39 years (Count)					0.884*** (0.341)
Log: Population 40 to 64 years (Count)					1.777*** (0.305)
Constant	-179.1*** (28.63)	-124.1*** (23.00)	-9.327** (4.358)	-12.67*** (4.047)	-142.5*** (28.23)
Month FE	**Yes**	**Yes**	**Yes**	**No**	**Yes**
State FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	30,216	30,216	29,853	30,216	30,216
R-squared	0.442	0.446	0.857	0.438	0.439

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. Regression of Total Pill Count per Capita on various specifications. Fixed effects are noted but not shown.

VARIABLES	(1) Original Model	(2) Border Binaries	(3) Lagged Variable	(4) Trend	(5) Alternative Age Specification
Female Population (Percent)	4.593** (1.979)	4.314** (1.989)	0.365** (0.164)	4.609** (1.980)	4.824** (1.994)
Log: Median Household Income	-0.395 (0.275)	-0.371 (0.278)	-0.0220 (0.0243)	-0.447* (0.271)	-0.0933 (0.250)
Log: Annual Population (Count)	0.220*** (0.0358)	0.226*** (0.0359)	0.0181*** (0.00364)	0.221*** (0.0358)	
Black Population (Percent)	-2.164*** (0.489)	-2.238*** (0.483)	-0.185*** (0.0468)	-2.143*** (0.488)	-2.292*** (0.492)
American Indian Population (Percent)	-0.235 (0.334)	-0.252 (0.330)	-0.0320 (0.0270)	-0.225 (0.334)	-0.203 (0.315)
Asian Population (Percent)	-6.526*** (1.969)	-6.770*** (1.992)	-0.609*** (0.169)	-6.467*** (1.962)	-7.821*** (1.884)
Pacific Islander Population (Percent)	9.616 (41.68)	11.59 (41.39)	2.112 (3.494)	7.611 (41.71)	11.43 (42.63)
All in Poverty (Percent)	0.0320*** (0.00915)	0.0331*** (0.00920)	0.00288*** (0.000824)	0.0301*** (0.00901)	0.0359*** (0.00957)
Population 0 to 19 years (Percent)	-2.903** (1.366)	-3.269** (1.338)	-0.264** (0.118)	-2.768** (1.355)	
Population 20 to 39 years (Percent)	3.835*** (1.398)	3.509** (1.379)	0.309** (0.125)	3.945*** (1.394)	
Population 40 to 64 years (Percent)	6.682*** (2.504)	6.171** (2.478)	0.522** (0.238)	6.809*** (2.499)	
Medical Marijuana Legal	0.0459** (0.0208)	-0.0224 (0.0153)	0.0103*** (0.00213)	0.0497** (0.0206)	0.0367* (0.0209)
Year	0.0763*** (0.00925)	0.0566*** (0.00761)	-0.00109 (0.000960)		0.0672*** (0.00924)
Distance: Nearest County Out of State (100 Miles)	0.0917 (0.0646)		0.00708 (0.00547)	0.0938 (0.0646)	0.0701 (0.0652)
Distance: Nearest Medical Marijuana (100 Miles)	0.0263*** (0.00630)		-0.00132** (0.000617)	0.0298*** (0.00604)	0.0227*** (0.00605)

Border Counties		-0.0913** (0.0435)			
Counties that border Marijuana Policy		-0.0732 (0.0754)			
Log: Lagged Total Pill Count (per Capita)			0.915*** (0.00949)		
Date				0.00686*** (0.000723)	
Log: Population 0 to 19 years (Count)					-1.438*** (0.281)
Log: Population 20 to 39 years (Count)					0.626*** (0.208)
Log: Population 40 to 64 years (Count)					1.037*** (0.214)
Constant	-155.9*** (16.65)	-116.1*** (13.20)	1.839 (1.821)	-6.143** (2.671)	-138.5*** (16.30)
Month FE	**Yes**	**Yes**	**Yes**	**No**	**Yes**
State FE	**Yes**	**Yes**	**Yes**	**Yes**	**Yes**
Observations	30,216	30,216	29,853	30,216	30,216
R-squared	0.435	0.438	0.923	0.429	0.437

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

and a 2.22% decrease in the total doses per capita, all else constant. These estimates are not significant but agree with the original estimates to measure doctor shopping.

Although this is a short time series of panel data, there is still concern of serial correlation affecting the accuracy of the estimated coefficients. By its nature, addiction may further confound this effect and drive some level of consistent monthly consumption of opioids among patients. Model (3) of tables 7 and 8 include a lagged dependent value to investigate the effect serial correlation may have on the original model. With this new specification, the majority of coefficients have the same sign as the original model, but all estimates become much smaller when the lagged value is included. The measured state effects also remain consistent but become smaller, indicating the majority of serial correlation is not the result of endogenous variables controlled for with fixed effects. This is consistent with Van Ours and Williams (2015) and without a strong instrumental variable for opioid consumption, this effect will bias all estimates.

Model (4) of each table considers a trend line in place of month fixed effects and a year indicator and finds an equivalent result to the original model, while Model (5) uses a logged measure of count for all age cohorts and drops the effect of total population, and again the coefficients of this model closely match those of the original model.

Discussion

The model predicts that further distance from a jurisdiction with legal marijuana is associated with increased opioid use which agrees with the predictions from theory. This suggests that as marijuana becomes easier (and therefore cheaper) to obtain, individuals with addictions may substitute to marijuana from opioids. This is consistent with Dragone et al. (2018), and confirms that access to marijuana depends on the distance to the nearest jurisdiction as this distance changes the cost of illegal procurement. For comparison, Dasgupta et al. (2013) estimate oxycodone had an average price of $10 per pill and hydrocodone had an average price of $8 per pill in 2012. At their means, the model estimates a $26,181 reduction in oxycodone sales ($\bar{g} = 1.075$ pills per capita) and a $59,108 reduction in hydrocodone sales ($\bar{g} = 2.107$ pills per capita) for a 100-mile decrease in the distance to a legal jurisdiction.[3] This change is measured between monthly observations and would represent an annual total difference of $1.023 million in opioid sales. These values represent a change in total consumption through pharmacies and does not specifically identify a reduction in addictive use or illegal diversion.

The positive estimates for the impact of MMLs on the demand for opioids capture the same endogeneity noted by Brinkman and Mok-Lamme (2017). While Brinkman and Mok-Lamme were able to find instrumental variables to control for the location of dispensaries, these same instruments do not hold for this study. States that pass medical marijuana laws by voter referenda may be more likely to treat pain as a community. These states may also be more likely to consider new alternatives for pain management, which could have affected early consumption of extended-release formulas when introduced causing higher and/or sustained consumption in later periods. Individual

---

[3] These interpretations were reached using the coefficient for the distance to the nearest medical marijuana jurisdiction in states that do not have MMLs. To reach this value, the expression $(e^{\beta} - 1)(\overline{pill\ count})(\overline{population})(price)$ where the average pill count and population were taken from the study states without medical marijuana laws.

patients in these states may be more likely to seek medical treatment in general. In all of these cases, this endogeneity indicates the model estimate is biased and the true effect of MMLs is likely different. This is also the result of the lack of data sets for marijuana use beyond those of categorical legal status. This result may also be the effect of this variable picking up additional trend effects over the study period within these states. While some states have implemented databases as part of their medical marijuana programs, these systems still face questions of how such information can be used and access to this data remains inconsistent even within states. Given potential endogeneity concerns, investigating an instrumental variable would shed invaluable light into the nature of the use of addictive substances. In states such as Colorado, Michigan, Illinois and Maine where marijuana is legal recreationally would make ideal candidates to investigate whether the per unit cost of electricity may be such a variable; these states have unideal agricultural conditions for growing marijuana outdoors for large portions of the year, but businesses involved in dispensing marijuana must source all product from within the state due to federal limitations on interstate trade. Many growing operations may rely on indoor greenhouse facilities which can take larger than usual amounts of electricity (an anomaly used to locate illegal growing operations in states where marijuana is not legal) and growers may attempt to schedule the growth of product around perceived trends in the cost of electricity in their states.

Finally, as part of the identification strategy this study controlled for potential effects of doctor shopping between jurisdictions by measuring each counties distance to the nearest state border. The model indicates that opioid usage increases with distance from the border in a state that has legalized marijuana use which is in conflict with prior research and the economic model proposed. Because doctor shoppers travel across state borders to bypass reporting systems, the distance to the border would represent some cost that varies based on the presumed distance travelled. Dragone et al. (2018) find the opposite effect with much stronger accuracy. Their study, which compared Washington and Oregon during the period when recreational marijuana was legalized, relied heavily on how similar these jurisdictions were and how close to passing or not each state was when voting to make this change. The states of this study do not share such similarities which may explain the differences in results. This can also be explained through the implementation of prescription monitoring programs in all of the states prior to the study period and discouraging such activity.

Conclusion

Shifting drug policy in the United States indicate shifting beliefs as new information becomes available and voters in each state reconsider the legality of marijuana. Recent studies have shown Marijuana can treat PTSD, chronic pain, anxiety, depression, and a large cohort of other chronic diseases that weigh down the modern medical system (Bowles, 2012; Bradford & Bradford, 2016; Lynch & Campbell, 2011). Simultaneously, medications once believed non-addictive have given rise to one of the largest drug pandemics in recent history (*HHS.Gov*). This problem has only intensified with the introduction of Fentanyl, a far more potent (2.4 mg morphine equivalence compared to oxycodone's 1.5 mg equivalence) and cheaper opioid which illegal drug markets have begun using to mask the impurity of other substances (Ehley, 2020). In response to this practice, fentanyl test strips have become available in some jurisdictions to allow individuals to test for the substance to prevent accidental overdose (Goldman et al., 2019). Another recent intervention to prevent overdose due to opioid use is the discovery of Naloxone, a medication which is sprayed into the nasal cavity during an overdose to block opioid receptors and reverse the effects of the drugs taken (SAMHSA HHS). Embracing this new medication, the chief medical official of numerous states including Montana and Wisconsin have issued standing orders to make Naloxone available without prescription at pharmacies within their state (*MT Standing Order*; *WI Standing Order*). Despite these interventions, the number of overdose deaths has begun to rise again as drug impurities cause more accidental overdoses (Ehley, 2020).

Policy makers will need sound knowledge on the true relationship between addictive substances to best address the shifting opinions and new information available. The rise of states considering or passing laws for medical and even recreational marijuana have introduced an unprecedented access to marijuana related product. While this study has investigated the nature between marijuana and opioids, further research will be crucial to empower future policy makers to define and regulate these new industries. By measuring the cost of travelling to different legal jurisdictions, this study confirms that pursuing new and thoughtful sources of data will only improve knowledge on how to understand the nature of addiction best.

Citations

About the Epidemic | HHS.gov. (n.d.). Retrieved November 12, 2019, from https://www.hhs.gov/opioids/about-the-epidemic/index.html

Alpert, A., Powell, D., & Pacula, R. L. (2018). Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids. *American Economic Journal. Economic Policy*, *10*(4), 1–35. http://dx.doi.org/10.1257/pol.20170082

Associated Press. (2011, August 25). *Police raid 2 Mich. Medical marijuana dispensaries*. https://advance-lexis-com.weblib.lib.umt.edu:2443/document?crid=f719c45c-1a81-41ce-8bed-2113c32acc3c&pddocfullpath=%2Fshared%2Fdocument%2Fnews%2Furn%3AcontentItem%3A53MV-MT11-JBGK-F338-00000-00&pdcontentcomponentid=304481&pdmfid=1516831&pdisurlapi=true

Bowles, D. W. (2012). Persons Registered for Medical Marijuana in the United States. *Journal of Palliative Medicine*, *15*(1), 9–11. https://doi.org/10.1089/jpm.2011.0356

Bowmaker, S. W. (2005). *Economics Uncut: A Complete Guide to Life, Death and Misadventure*. Edward Elgar Publishing, Inc.

Bradford, A. C., & Bradford, W. D. (2016). Medical Marijuana Laws Reduce Prescription Medication Use In Medicare Part D. *Health Affairs*, *35*(7), 1230–1236. https://doi.org/10.1377/hlthaff.2015.1661

Bretteville-Jensen, A. L., & Biørn, E. (2004). Do prices count? A micro-econometric study of illicit drug consumption based on self-reported data. *Empirical Economics*, *29*(3), 673–695. https://doi.org/10.1007/s00181-004-0205-9

Brinkman, J., & Mok-Lamme, D. (2017). *Not in My Backyard? Not So Fast. The Effect of Marijuana Legalization on Neighborhood Crime* (Working Paper (Federal Reserve Bank of Philadelphia) No. 17–19). Federal Reserve Bank of Philadelphia. https://doi.org/10.21799/frbp.wp.2017.19

Buchmueller, T. C., & Carey, C. (2018). The Effect of Prescription Drug Monitoring Programs on Opioid Utilization in Medicare. *American Economic Journal. Economic Policy*, *10*(1), 77–112. http://dx.doi.org.weblib.lib.umt.edu:8080/10.1257/pol.20160094

Bulloch, M. (2018, July 26). *The Evolution of the PDMP*. Pharmacy Times. https://www.pharmacytimes.com/contributor/marilyn-bulloch-pharmd-bcps/2018/07/the-evolution-of-the-pdmp

Cicero, T. J., & Ellis, M. S. (2015). Abuse-Deterrent Formulations and the Prescription Opioid Abuse Epidemic in the United States: Lessons Learned From OxyContin. *JAMA Psychiatry*, *72*(5), 424–430. https://doi.org/10.1001/jamapsychiatry.2014.3043

Cicero, T. J., Inciardi, J. A., & Muñoz, A. (2005). Trends in Abuse of OxyContin® and Other Opioid Analgesics in the United States: 2002-2004. *The Journal of Pain*, *6*(10), 662–672. https://doi.org/10.1016/j.jpain.2005.05.004

Colin Cameron, A., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372. https://doi.org/10.3368/jhr.50.2.317

Dasgupta, N., Freifeld, C., Brownstein, J. S., Menone, C. M., Surratt, H. L., Poppish, L., Green, J. L., Lavonas, E. J., & Dart, R. C. (2013). Crowdsourcing Black Market Prices For Prescription Opioids. *Journal of Medical Internet Research*, *15*(8), e178. https://doi.org/10.2196/jmir.2810

Dragone, D., Prarolo, G., Vanin, P., & Zanella, G. (2018). Crime and the legalization of recreational marijuana. *Journal of Economic Behavior & Organization*. https://doi.org/10.1016/j.jebo.2018.02.005

Drilling into the DEA's pain pill database. (n.d.). Washington Post. Retrieved October 15, 2019, from https://www.washingtonpost.com/graphics/2019/investigations/dea-pain-pill-database/

Drug Overdose Deaths | Drug Overdose | CDC Injury Center. (2019, August 30). https://www.cdc.gov/drugoverdose/data/statedeaths.html

Ehley, B. (2020, July 15). *Fatal overdoses climbed to record high in 2019, reversing historic progress*. POLITICO. https://www.politico.com/news/2020/07/15/drug-overdoses-record-high-363719

Goldman, J. E., Waye, K. M., Periera, K. A., Krieger, M. S., Yedinak, J. L., & Marshall, B. D. L. (2019). Perspectives on rapid fentanyl test strips as a harm reduction practice among young adults who use drugs: A qualitative study. *Harm Reduction Journal*, *16*(1), 3. https://doi.org/10.1186/s12954-018-0276-0

Hassan, A. (2019, October 2). *A Doctor Who Prescribed 500,000 Doses of Opioids Is Sent to Prison for 40 Years* [News Publisher]. The New York Times. https://www.nytimes.com/2019/10/02/us/opioids-doctor-sentenced-joel-smithers.html

Jones, M. R., Viswanath, O., Peck, J., Kaye, A. D., Gill, J. S., & Simopoulos, T. T. (2018). A Brief History of the Opioid Epidemic and Strategies for Pain Medicine. *Pain and Therapy*, *7*(1), 13–21. https://doi.org/10.1007/s40122-018-0097-6

Kelly, C. R. (2019). *The Effect of Health Care Access on Opioid Overdoses at the County Level in the United States* [M.P.P., Georgetown University]. http://search.proquest.com/docview/2240072999/abstract/A9E8698A1A1F4203PQ/1

Lynch, M. E., & Campbell, F. (2011). Cannabinoids for treatment of chronic non-cancer pain; a systematic review of randomized trials. *British Journal of Clinical Pharmacology*, *72*(5), 735–744. https://doi.org/10.1111/j.1365-2125.2011.03970.x

Meier, B. (2007, May 10). In Guilty Plea, OxyContin Maker to Pay $600 Million. *The New York Times*. https://www.nytimes.com/2007/05/10/business/11drug-web.html

MT Standing Order. (n.d.). 2.

Murphy, S. M., Friesner, D. L., & Rosenman, R. (2015). Opioid Misuse Among Adolescents: New Evidence from a Misclassification Analysis. *Applied Health Economics and Health Policy; Auckland*, *13*(2), 181–192.

Newton, D. (2018). *The Opioid Crisis: A reference handbook*. ABC-CLIO.

Offit, P. A. (2017). *Pandora's Lab*. National Geographic.

Pacula, Rosalie L., Powell, D., Heaton, P., & Sevigny, E. L. (2015). Assessing the Effects of Medical Marijuana Laws on Marijuana Use: The Devil is in the Details. *Journal of Policy Analysis and Management*, *34*(1), 7–31. https://doi.org/10.1002/pam.21804

Pacula, Rosalie Liccardo, Hunt, P., & Boustead, A. (2014). Words Can Be Deceiving: A Review of Variation Among Legally Effective Medical Marijuana Laws in the United States. *Journal of Drug Policy Analysis*, *7*(1), 1–19. https://doi.org/10.1515/jdpa-2014-0001

PDMP Center of Excellence. (2014). *Briefing on PDMP Effectiveness*. Brandeis University.

Powell, D., Pacula, R. L., & Jacobson, M. (2018). Do medical marijuana laws reduce addictions and deaths related to pain killers? *Journal of Health Economics*, *58*, 29–42. https://doi.org/10.1016/j.jhealeco.2017.12.007

Prescription Drug Monitoring Frequently Asked Questions (FAQ) | The PDMP Training and Technical Assistance Center. (n.d.). Retrieved January 11, 2020, from http://www.pdmpassist.org/content/prescription-drug-monitoring-frequently-asked-questions-faq

Sabia, J. J., & Nguyen, T. T. (2018). The Effect of Medical Marijuana Laws on Labor Market Outcomes. *The Journal of Law and Economics*, *61*(3), 361–396. https://doi.org/10.1086/701193

Saffer, H., & Chaloupka, F. (1999). THE DEMAND for ILLICIT DRUGS. *Economic Inquiry*, *37*(3), 401–411. https://doi.org/10.1111/j.1465-7295.1999.tb01439.x

SAMHSA HHS. (n.d.). *Naloxone*. Retrieved July 31, 2020, from https://www.samhsa.gov/medication-assisted-treatment/treatment/naloxone

Shi, Y. (2017). Medical marijuana policies and hospitalizations related to marijuana and opioid pain reliever. *Drug and Alcohol Dependence*, *173*, 144–150. https://doi.org/10.1016/j.drugalcdep.2017.01.006

The Huffington Post. (2013, February 8). *Michigan Medical Marijuana Dispensaries Illegal, State Supreme Court Rules 4-1*. https://advance-lexis-com.weblib.lib.umt.edu:2443/document?crid=523cfb6d-590b-4417-961c-a97cf571b8d5&pddocfullpath=%2Fshared%2Fdocument%2Fnews%2Furn%3AcontentItem%3A57PD-7J21-JCMN-Y0TD-00000-00&pdcontentcomponentid=299488&pdmfid=1516831&pdisurlapi=true

Timeline of Selected FDA Activities and Significant Events Addressing Opioid Misuse and Abuse. (2019). US Food and Drug Administration.

US GAO. (2011). *MEDICARE PART D: Instances of Questionable Access to Prescription Drugs*. United States Government Accountability Office.

van Ours, J. C. (1995). The Price Elasticity of Hard Drugs: The Case of Opium in the Dutch East Indies, 1923-1938. *Journal of Political Economy*, *103*(2), 261–279.

Van Ours, J. C., & Williams, J. (2015). Cannabis Use and Its Effects on Health, Education and Labor Market Success. *Journal of Economic Surveys*, *29*(5), 993–1010. https://doi.org/10.1111/joes.12070

WI Standing Order. (2016, August 22). Wisconsin Department of Health Services. https://www.dhs.wisconsin.gov/opioids/standing-order.htm