Marijuana De-regulation and Automobile Accidents: Evidence from Auto Insurance
Working Paper

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Abstract

The legal status of marijuana has transformed radically over the past two decades. Prior to 1996, marijuana was illegal across the country. Then, California started a trend that has seen marijuana legalized for medical purposes in 34 states and additionally for recreational purposes in 9 of those. While the public benefits of legalizing marijuana are well-documented, much of the potential public detriment remains under-studied. We focus on one potential detriment – the effect of marijuana legalization on automobile safety. Experimental studies show that marijuana negatively impacts driving ability. Given this, it is natural to assume that increasing access to marijuana would lead to an increase in car accidents, but the reality is unclear. Alcohol by itself is more detrimental to driving than the use of marijuana by itself. If marijuana and alcohol are substitutes, then lowering the absolute price of marijuana could lead people away from alcohol. Even with an increase in marijuana-related accidents, the total number of accidents could be reduced. We examine this question through the effect on the auto insurance market using localized, at the zip-code level, data on auto insurance premiums. We find that the legalization of medical marijuana leads to a decrease in auto insurance premiums of $5.20 per policy per year. This effect is stronger in areas close to a dispensary. We find limited evidence that the reduction is due to a decrease in drunk driving prior to legalization.

JEL Codes: **G22, G28, I18, K42, P37**

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1 Introduction:

The legal status of marijuana has experienced a radical transformation over the past two decades. Prior to 1996, marijuana was illegal across the country. California, with approval of Proposition 215, started a trend that has seen marijuana legalized solely for medical purposes in 23 states (including Washington DC) and for recreational purposes in 11 states. While the direct public benefits of legalizing marijuana are well-documented (though still politically controversial), much of the potential public detriment remains under-studied. In this article, we focus on one potential detriment – the effect of increased marijuana access on auto safety. The idea is that decreasing the absolute price, through legalization, of marijuana increases driving under the influence of the drug which increases automobile accidents. At first glance, this makes sense – experimental studies show that marijuana negatively impacts driving ability (e.g. Lenné et al., 2010; Hartman and Huestis, 2013). It is natural to assume that increasing access to marijuana would lead to an increase in car accidents, but reality is less clear.

It is also generally accepted that the use of alcohol by itself is more detrimental to driving than the use of marijuana by itself (e.g. Chihuri et al., 2017). If marijuana and alcohol are substitutes, as suggested by Chaloupka and Laixuthai (1997) and Anderson et al. (2013), then lowering the absolute price of marijuana could lead people away from alcohol and, even though there may be an increase in marijuana-related accidents, the total number and cost of accidents could be reduced. We examine the effect of legalization on auto accidents through the direct effect on auto insurance premiums. We use two separate identification channels: a geographic discontinuity across state borders using localized, at the zip-code level, survey data on auto insurance premiums and a heterogeneous treatment difference-in-differences design using the same localized premium data and hand-collected data on the location of medicinal marijuana dispensaries. We find that the legalization of medical marijuana leads to a decrease in auto insurance premiums of $5.20 per policy per year. This implies that legalization makes the roads safer, counter to initial intuition. The effect is stronger in areas close to a dispensary. We find limited evidence that the reduction is due to a decrease in drunk driving.

Although prohibition of marijuana began decades earlier, the classification of marijuana as a Schedule I drug in the Controlled Substances Act of 1970 reinforced the illegality of the drug and influenced cannabis-related legislation and policies for the next 40 years. Strict prohibition of a good increases the non-pecuniary costs (Thornton, 2014). The recent rise of medical-use marijuana laws have relaxed this constraint – leading to a decrease in absolute price and thus an increase in consumption via both illicit (Pacula et al., 2015) and now-legal use (Alford, 2015; Anderson et al., 2013; Cerdá et al., 2012; Chu, 2014; Wen et al., 2015). Marijuana impairs cognitive and psychomotor skills, and acute usage has been found to significantly increase the risk of motor vehicle collisions in controlled trials (Ramaekers et al., 2004; Bondallaz et al., 2016). Thus, increased access to marijuana, via decreased non-pecuniary costs, should increase the risk of traffic crashes, *ceteris paribus* (Asbridge et al., 2012; Hartman and Huestis, 2013).

However, life is not *ceteris paribus*. The true effect of medical marijuana laws on traffic safety is unclear and empirical evidence is mixed. First, laws typically restrict consumption to a private residence, as opposed to a bar, thus reducing travel and limiting exposure to risk of being involved in a traffic crash. Santaella-Tenorio et al. (2017) find that states who enact medical marijuana laws are associated with lower traffic fatality rates than states without medical marijuana laws with immediate reductions occurring in fatality rates for those aged 15-24 and 25-44. Second, marijuana consumption may be a substitute for other intoxicating substances. For instance, Anderson et al. (2013) find that medical marijuana laws are associated with fewer alcohol-related deaths and Kim et al. (2016) find reductions in tests of positive opioid use of deceased drivers following implementation of medical marijuana laws. Baggio et al. (2018) find that legalization of medical marijuana directly lowers demand for alcohol. Smart (2015) argues that greater marijuana access decreases traffic crash mortality in the aggregate but increases traffic fatalities caused by drivers aged 15-20, who are not able to legally drink alcohol.[1]

Because of data availability, the majority of extant studies examining marijuana and automobiles only look at fatal car crashes. This is a large shortcoming. In 2016, there were around 7,277,000 auto accidents reported to police of which only 34,439 resulted in fatalities (FARS, 2018). The existing literature misses over 99.5% of auto crashes. We instead approach the question through a different avenue – the direct effect on auto insurance premiums. Auto insurers cover 67% of all

[1] In the short time following legal recreational sales, Hansen et al. (2018) fail to find any evidence of recreational marijuana laws increasing fatal traffic crashes.

medical and property damage from automobile accidents (Blincoe et al., 2015). Through this lens we paint a more comprehensive picture.

We make use of two identification strategies. Our first specification uses zip-code level data on auto insurance premiums. The identification lies in a quirk of medicinal marijuana laws (but not recreational) – you have to physically live in the state in order to acquire a medical marijuana card. Prior to Nevada's legalization, if you lived on the western shore of Lake Tahoe (in California), you could legally purchase marijuana with a California prescription card (which were notoriously easy to acquire) – if you lived on the eastern shore (in Nevada), you were out of luck. This creates a sharp geographic discontinuity in policy at the state border that coincides with a sharp geographic discontinuity in auto insurance rate setting, while maintaining a similar driving environment. We exploit this geographic discontinuity by comparing paired collections of zip codes near the border in a difference-in-differences design.[2] Table 1 shows the timeline of medical marijuana laws in the United States. Our identification is based on the states in bold.[3]

Table 1: Timeline of Medical Marijuana Laws

State	Law Passed	Law Beginning	First Dispensary	State	Law Passed	Law Beginning	First Dispensary
Alaska	1998	1999	-	Montana	2004	2004	2011
Alabama	-	-	-	North Carolina	-	-	-
Arkansas	2016	2016	-	North Dakota	2016	2016	-
Arizona	2010	2010	2012	Nebraska	-	-	-
California	1996	1996	1997	**New Hampshire**	**2013**	**2013**	**2016**
Colorado	2000	2001	2005	New Jersey	2010	2010	2012
Connecticut	**2012**	**2012**	**2014**	New Mexico	2007	2007	2010
DC	2010	2010	-	Nevada	2000	2001	2010
Delaware	**2011**	**2011**	**2015**	**New York**	**2014**	**2014**	**2016**
Florida	**2016**	**2017**	**2016**	Ohio	2016	2016	-
Georgia	-	-	-	Oklahoma	2018	2018	-
Hawaii	2000	2000	-	Oregon	1998	1998	2010
Iowa	-	-	-	Pennsylvania	2016	2016	2018
Idaho	-	-	-	Rhode Island	2006	2006	2013
Illinois	**2013**	**2014**	**2015**	South Carolina	-	-	-
Indiana	-	-	-	South Dakota	-	-	-
Kansas	-	-	-	Tennessee	-	-	-
Kentucky	-	-	-	Texas	-	-	-
Louisiana	2016	2016	-	Utah	2018	2018	-
Massachusetts	**2012**	**2013**	**2015**	Virginia	-	-	-
Maryland	**2014**	**2014**	**2017**	Vermont	2004	2004	2013
Maine	1999	1999	2011	Washington	1998	1998	2010
Michigan	2008	2008	2010	Wisconsin	-	-	-
Minnesota	**2014**	**2014**	**2015**	West Virginia	2017	2019	-
Missouri	2018	2018	-	Wyoming	-	-	-
Mississippi	-	-	-				

Note: This table represents the history of medical marijuana laws in the US. Treatment states are in bold.

[2]This approach has precedent (though with counties). See Gowrisankaran and Krainer (2011); Dube et al. (2010); Baggio et al. (2018) for example.

[3]Our zip data are from 2014-2018. We define a state as "treated" once it has had a dispensary open for at least one year.

Our second specification combines our zip code premium data with hand-collected data on medical marijuana dispensary location and opening dates. Increases in marijuana consumption are driven largely by the local presence of legal dispensaries (Pacula et al., 2015). Thus, those localities near a dispensary have their absolute price lowered by more than localities that are further away. We exploit this using a heterogeneous treatment difference-in-differences estimation where we classify zip codes near a dispensary as our "heavily-treated" group, zip codes in states that legalize but are far from dispensaries as our treated group, and zip codes in states that have not expanded as our control group.

A potential issue with inferring a reduction in premiums as an increase in auto safety is that we are ignoring potential demand side effects. If insurers are reducing premiums in response to preference-driven demand changes, and not cost-driven supply changes, then we should see a reduction in firm profits. We address this through firm-state level data on premiums and losses for every auto insurer in the United States. Following Karl and Nyce (2017), who estimate the effect of hand-held cellphone bans while driving, we estimate the impact of medical marijuana implementation (in difference-in-differences framework) on insurance profits and fail to find a negative effect.[4]

This paper contributes to the growing literature on spillover effects of medicinal marijuana legalization as well as contributing to a greater understanding of the factors influencing auto insurance pricing. Through our focus on auto insurance, we are able to examine the effect on a majority of auto accidents, rather than the 0.5% that result in fatalities. We find that the legalization of medical marijuana leads to a decrease in auto accidents premiums and that this effect is larger in areas that had high levels of driving under the influence (DUI) prior to legalization.

2 Discussion of Data:

We use two levels of automobile insurance data – zip-code level survey data on auto insurance premiums from the S&P Global Market Intelligence database and firm-state level financial data on auto insurers from the National Association of Insurance Commissioners' (NAIC) Property-Liability database.

[4]Our point estimate actually points to an increase in insurer profits, making our estimated effect via premiums likely a conservative estimate of the true cost effect.

2.1 Survey and Dispensary Data:

Our main dataset is a yearly market research survey conducted by Nielsen and available through the S&P Global Market Intelligence Platform. The zip-code level survey data contain the average annual premiums for automobile insurance in the zip code, the number of households with automobile insurance, and the number of households purchasing auto insurance from each of the top fifteen major auto insurers.[5] The survey also contains a number of demographic variables calculated from the American Community Survey (ACS).[6] For our geographic discontinuity approach, we obtain pairs of near (across state lines) zip-codes for states that expanded from 2015 - 2018.[7]

Table 2 shows univariate summary statistics for states that ever legalize medical marijuana vs. the ones that do not. As expected, the states that eventually legalize are quite different than those that never do. Legalization states are richer and denser while those who never legalize tend to have larger incidences of DUI on a per capita basis. Tables 3 and 4 present summary statistics for our matched border samples in 2014. Table 3 compares zip codes in those states who legalize post 2014, and thus we observe them switch, to those who never legalize and Table 4 compares the switching group to those who had already legalized by 2014. Ideally, we would like the covariates to balance across both samples. However, this does not appear to be the case. While the difference in means for most variables is less (in absolute value) than the difference in means from the all zip code sample (Table 2), the difference does remain significant for most of the variables. It is important to note that our identification is based on parallel trends and not parallel base levels, so this does not necessarily mute our analysis.

We derive the time-line of marijuana legalization state by state through ProCon.org (2018a). Because legal and active dispensaries drive the increase in cannabis consumption following medical marijuana law enactments, we follow the literature and base our treatment on the opening of the first dispensary (Pacula et al., 2015). Prior to dispensaries opening, there were few other ways to acquire marijuana which varied from state to state. Some states allowed caregivers to

[5] The data also contain a number of other survey items we do not use such as "did you switch plans" and "how many claims have you had in the past 3 years."

[6] The 2017 and 2018 ACS control variables are projected by the survey.

[7] Each zip code is paired with every zip code across the state border within 25 miles. The same zip code can be in several pairs. We account for this through multi-way clustered standard errors which are described in the next section. The distances between zip codes are obtained from the NBER database at http://www.nber.org/data/zip-code-distance-database.html.

Table 2: All Zip Code Summary Statistics

Variable	Full Sample:		Ever Legalize:		Never Legalize:		Diff. Means:	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Diff.	t
Unemployment Rate	8.326	4.586	8.689	4.585	8.108	4.572	0.581	23.816
Average Age	41.960	6.566	42.646	7.101	41.551	6.189	1.095	30.261
Population Density	1305.995	5220.690	2284.708	8030.801	716.469	1975.138	1568.239	45.625
Average Income	54869.773	21774.315	61219.882	25529.495	51044.793	18116.536	10175.089	83.041
Average Premium	3743.001	5067.426	4316.339	5567.667	3397.627	4707.124	918.712	32.816
Num. Under 25	1224.470	168.497	1251.013	202.894	1208.480	141.477	42.533	43.855
Num. Insured	599.453	881.157	685.942	943.843	547.353	836.846	138.590	28.773
log(Registered Patients)	2.537	4.641	6.739	5.377	0.000	0.000	6.739	300.016
DUI per Capita Pre-Expansion	0.006	0.012	0.005	0.007	0.006	0.013	−0.002	−25.613
N	152260		57310		94950		-	

Note: This table presents summary statistics for all of the zip codes in our data separated by treatment vs. control states.

Table 3: Border Zip Code Summary Statistics: Treat vs. Control

Variable	Full Sample:		Legalize Post 2014:		Never Legalize:		Diff. Means:	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Diff.	t
Unemployment Rate	8.658	4.457	8.119	3.182	9.173	5.350	−1.054	−12.346
Average Age	42.686	4.761	43.104	4.561	42.287	4.912	0.817	8.848
Population Density	857.984	2445.253	416.209	865.127	1279.585	3257.025	−863.376	−18.774
Average Income	61259.829	24206.713	63548.695	23772.310	59075.484	24417.026	4473.211	9.524
Average Premium	3400.156	4269.912	2801.180	3789.622	3971.779	4610.899	−1170.599	−14.259
Num. Under 25	1266.209	139.268	1280.060	138.802	1252.990	138.437	27.070	10.016
Num. Insured	473.228	617.155	390.561	536.022	552.120	676.381	−161.559	−13.615
DUI per Capita Pre-Expansion	0.004	0.002	0.004	0.002	0.004	0.002	0.000	2.731
N	10528		5141		5387		-	

Note: This table presents summary statistics for the paired border zip codes in our data separated by treatment vs. control states in 2014.

Table 4: Border Zip Code Summary Statistics: Treat vs. Always Treated

Variable	Full Sample:		Legalize Post 2014:		Legalize Pre 2014:		Diff. Means:	
	Mean	St. Dev.	Mean	St. Dev.	Mean	St. Dev.	Diff.	t
Unemployment Rate	8.722	4.079	8.119	3.182	11.275	6.018	−3.155	−17.686
Average Age	42.949	4.663	43.104	4.561	42.294	5.019	0.810	5.144
Population Density	646.025	1434.719	416.209	865.127	1620.044	2538.128	−1203.835	−16.297
Average Income	63720.117	23693.469	63548.695	23772.310	64446.647	23352.093	−897.952	−1.200
Average Premium	2825.354	3624.929	2801.180	3789.622	2927.811	2821.217	−126.631	−1.309
Num. Under 25	1291.123	136.263	1280.060	138.802	1338.011	113.589	−57.950	−15.280
Num. Insured	392.623	512.321	390.561	536.022	401.364	396.511	−10.803	−0.793
log(Registered Patients)	0.004	0.003	0.004	0.002	0.005	0.003	−0.001	−12.274
N	6354		5141		1213		-	

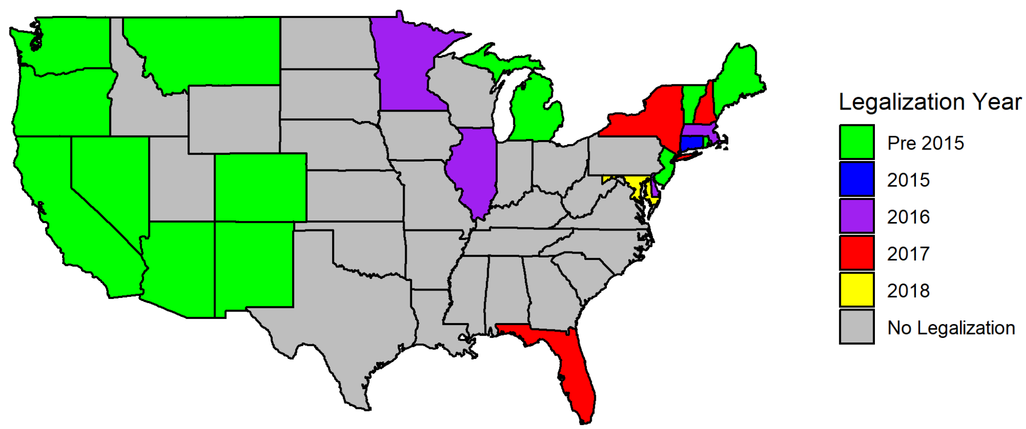
Note: This table presents summary statistics for the paired border zip codes in our data separated by treatment vs. always treated states in 2014.

directly administer the drug and some allowed self cultivation. In this paper, we focus on exposure to dispensaries.[8] To track the first dispensary openings, we searched the ProCon website, news

[8] Usually, a state does not immediately issue the licenses for growing or selling marijuana after its legalization. The time between a state legalizing medical marijuana and the first dispensary opening can be quite long; Maine, Oregon, and Washington took 12 years to open their first dispensary.

articles, and state records. We then cross-referenced our opening dates with the online appendix provided by Smith (2017). To account for a lag in the effect of the first dispensary opening and a lag in auto insurance premium rate setting, we follow the literature and define a state as being "treated" once a dispensary has been open for at least 1 year. For the remainder of this paper, we define a state as having "legalized medical marijuana" when that state has had a dispensary open for at least 1 year and not before. Figure 1 shows the year of treatment for each state. The green and gray states are the pre-treated and non-treated (respectively) control groups.

Figure 1: Map of Marijuana Legalization



We match our zip-code level insurance survey data with hand collected data on medical marijuana dispensary openings. Dispensary information is gathered from state registries and includes the name of the business and the address of the establishment. All state medical marijuana laws enacted after 2010 include explicit provisions regarding dispensary operations. Therefore, measurement error in the dispensary variable is likely minimal given the licensing process and the records maintained by each respective state of ongoing dispensary operations. However, the potential for measurement error does emerge from possible incorrectly reported opening dates as well as dispensaries that may have closed. Because it is more likely dispensary operations were missed rather than non-dispensary areas being classified as "treated," any measurement error in the dispensary variable would bias the results towards zero and thus makes our estimated effects on traffic safety conservative.[9]

[9]See Smith (2017) for documentation of marijuana-locating websites and state-specific sources.

2.2 NAIC Data:

The NAIC data (1993 - 2015) contain the financial operations of virtually all of the automobile insurers operating in the United States. From this database, we obtain the dollar amount of premiums earned (*Premiums*) and incurred losses (*Losses*) by a given auto insurer, in a given state, during a given year.[10] We then divide *Losses* by *Premiums* to obtain the *Loss Ratio*. The *Loss Ratio*, which is the ratio of incurred losses to premiums earned, is a commonly used ex post measure of the inverse underwriting profit for the insurance per dollar of losses paid (e.g. Grace and Leverty, 2012).

Our analysis hinges on any potential demand-side effects being orthogonal to the medical marijuana based supply-side effects we are trying to identify. The *Loss Ratio* allows us to check this. In our local analysis, we find premiums fall in response to medical marijuana laws. If the *Loss Ratio* is also going down, then premiums are falling slower than costs and we are under-estimating the true effect; if the *Loss Ratio* is going up, then premiums are falling faster than costs and our estimate is biased away from zero; if the *Loss Ratio* is unchanging, then premiums and costs are moving hand-in-hand and our estimate is free from confounding demand-side factors.

For control variables, we also obtain total admitted assets, organizational form, and the number of states the firm operates in. We merge this with the Best Key Rating Guide for the firm's primary distribution system (marketing type) and financial strength rating. We also merge the NAIC data with state-level controls from other various sources. The Federal Highway Administration's Highway Statistics Series Publications provide the numbers of licensed drivers and young drivers aging 19 or under, and the state gas tax rate. The state unemployment rate is from the Bureau of Labor Statistics. Per-capita personal income is available through the Bureau of Economic Analysis. Our tort-reform controls come from the Database of State Tort Law Reforms (DSTLR) and American Tort Reform Association (ATRA) Tort Reform Record. The DSTLR only has data up to 2012; after that, we obtain tort reform data from the ATRA record. Strict rate regulation data are obtained and cross-checked from multiple sources, including Harrington (2002), NAIC Auto

[10] Incurred losses include loss adjustment expenses.

Database Report (2000-2015), and state laws for various years. A state has strict rate regulation if the insurance rate is state-made or needs prior approval.[11]

2.3 Other Data:

We also hand-collect the number of medical marijuana registered patients in the states that have legalized the medical marijuana during 2013 to 2018. A registered patient is a person who applied and has been approved for a medical marijuana program certification card for legally purchasing and using marijuana for medical purposes.[12] We searched each state's medical marijuana program page, which is often under the state's department of health website. These programs provide medical marijuana statistic reports on a weekly, monthly, or annual basis; we look for the number of qualifying patients as of the latest date of the year.[13] California and Washington do not have mandatory registration requirement; as a result, their numbers of registered patients are under-reported. For these two states, we use the data from ProCon.org (2018b), ProCon.org (2016), and ProCon.org (2014) that estimate the per capita patient number of California based on Arizona and Maine and estimate Washington using Oregon.[14]

To capture changes in driver alcohol usage and driving under influence (DUI) after medical marijuana legalization, we use the number of DUI arrests from the Federal Bureau of Investigation's (FBI) Uniform Crime Reports (UCR) that are available for 2009 to 2016.[15] DUI is defined in UCR Handbook (Federal Bureau of Investigation, 2004) as "driving or operating a motor vehicle or common carrier while mentally or physically impaired as the result of consuming an alcoholic beverage or using a drug or narcotic." The vast majority of DUIs are due to alcohol. UCR reports provide the county-level data on the counts of arrests by demographic group and offense and includes DUI offenses on a monthly basis. Two drawbacks of the UCR are that the data are just arrest counts and not necessarily crime counts and that not all agencies participate.

[11] A state-made rate is one that is imposed by the state often in a public utility style rate hearing. Massachusetts undertook rate regulation like this until recently. Prior approval laws require the insure to seek approval prior to the rate being used. In this process, the state looks at the assumptions the insurer uses to set rates. Often the state's response is to approve a rate lower than initially requested.

[12] A qualifying patient's certification card is re-certified every year conditional on the re-evaluation of the patient's medical condition by a health practitioner.

[13] Some states report the medical marijuana statistics on a fiscal-year basis, e.g., Minnesota. In this case, the number of registered patients is as of June 30.

[14] This does not impact our main results as California is not a "border state" for our purposes.

[15] The series of UCR reports include Federal Bureau of Investigation (2009) through Federal Bureau of Investigation (2016).

3 Methods and Results:

3.1 Full Sample Analysis:

Our first approach uses a difference-in-differences strategy for all zip codes in the continental US. This identification is based on the "treatment" of Connecticut in 2015; Delaware, Illinois, Massachusetts, and Minnesota in 2016; Florida, New Hampshire, and New York in 2017; and Maryland in 2018. Specifically, we estimate

$$y_{zt} = \beta_1 Medical\_Marijuana_{st} + x'_{zt}\beta_2 + Own\_Zip_z + Year_t + \epsilon_{zt} \tag{1}$$

$$y_{zt} = \beta_1 Registered\_Patients_{st} + x'_{zt}\beta_2 + Own\_Zip_z + Year_t + \epsilon_{zt} \tag{2}$$

$$\begin{aligned} y_{zt} = {} & \beta_1 Medical\_Marijuana_{st} + \beta_2 Medical\_Marijuana_{st} : DUI_{z(t^*-1)} + x'_{zt}\beta_3 \\ & + Own\_Zip_z + Year_t + \epsilon_{zt} \end{aligned} \tag{3}$$

$$\begin{aligned} y_{zt} = {} & \beta_1 Medical\_Marijuana_{st} + \beta_2 Medical\_Marijuana_{st} : Smoking_s + x'_{zt}\beta_3 \\ & + Own\_Zip_z + Year_t + \epsilon_{zt} \end{aligned} \tag{4}$$

Where y_{zt} is the average annual auto insurance premium for zip code z in year t; $Medical\_Marijuana_{st}$ is the binary treatment variable for when state s legalizes medical marijuana (i.e. has a dispensary open for at least 1 year); x_{zt} is a vector of zip-code level controls (inclusive of an intercept); Own_Zip_z is a vector of zip code fixed effects; $Year_t$ is a vector of year fixed effects; $DUI_{z(t^*-1)}$ is the number of DUI arrests per capita in the county of zip code z in the year prior to legalization; $Smoking_s$ is a binary variable for if the state allows smoking as a method of consumption; and ϵ_{zt} is the mean-zero error term. Because our treatment is applied at the state level, standard errors for all models presented are clustered by state.

The results of our all zip code analysis (Equations (1) - (4)) are presented in Table 5. The first column of Table 5, which uses a binary treatment variable, shows that legalizing medical marijuana reduces average annual auto insurance premiums by \$9.60. The second column of Table 5 uses the log of the number of registered patients as a continuous treatment. We find that increasing the number of registered users by 1% decreases auto insurance premiums by 1.04% per year. Auto insurance premiums are largely driven by costs.[16] This implies that legalizing marijuana has a positive impact on auto safety. The third column of Table 5 interacts the binary treatment variable with the number of DUI arrests per capita in the year prior to legalization. We find the negative effect of legalization on premiums is much higher in areas that had relatively more issues with drunk driving prior to legalization. The fourth column of Table 5 checks for a heterogeneous treatment effect in states that allow smoking as a method of consumption, but we are unable to distinguish a differential effect.

[16] In prior approval states they are legally mandated to be. This will also be the case when markets are competitive.

Table 5: All Zips Diff-in-Diff

	Dependent variable:			
	Annual Premiums	Annual Premiums	Annual Premiums	Annual Premiums
	(1)	(2)	(3)	(4)
Medical Marijuana Legalization	-9.597^{*}		12.225^{***}	
	(5.645)		(3.549)	
ln(Number Registered)		-1.044^{**}		
		(0.488)		
Medical Marijuana Legalization : DUI_{t*-1}			-132.257^{*}	
			(72.414)	
Medical Marijuana Legalization : Smoking Allowed				-6.859
				(5.760)
Medical Marijuana Legalization : Smoking Not Allowed				-12.166
				(8.799)
Median Age	0.337	0.323	0.104	0.329
	(0.314)	(0.312)	(0.092)	(0.315)
Population with Bachelor's Degree	0.165	0.171	0.253^{**}	0.159
	(0.188)	(0.182)	(0.101)	(0.187)
Unemployment	0.283^{*}	0.300^{*}	0.182^{**}	0.284^{*}
	(0.162)	(0.167)	(0.089)	(0.162)
Population Density (#/sq. mi.)	0.011^{**}	0.010^{**}	0.013^{*}	0.011^{**}
	(0.005)	(0.005)	(0.007)	(0.005)
Median Household Income	0.001^{***}	0.001^{***}	0.000	0.001^{***}
	(0.000)	(0.000)	(0.000)	(0.000)
Drivers Under 25 on Policy	-0.177^{***}	-0.175^{***}	0.006	-0.177^{***}
	(0.028)	(0.028)	(0.026)	(0.028)
Number Insured	0.451^{***}	0.452^{***}	0.483^{***}	0.451^{***}
	(0.034)	(0.033)	(0.047)	(0.034)
Primary Insurer - AAA	0.086^{**}	0.086^{**}	1.224^{***}	0.085^{**}
	(0.039)	(0.038)	(0.233)	(0.039)
Primary Insurer - Allstate	0.219	0.231	0.911^{***}	0.223
	(0.196)	(0.197)	(0.352)	(0.196)
Primary Insurer - American Family	-1.625^{***}	-1.616^{***}	0.234	-1.615^{***}
	(0.420)	(0.417)	(0.295)	(0.420)
Primary Insurer - Farm Bureau	0.375	0.392	-1.014^{***}	0.383
	(0.615)	(0.609)	(0.387)	(0.619)
Primary Insurer - Farmers	1.297^{***}	1.288^{***}	0.819^{***}	1.296^{***}
	(0.257)	(0.258)	(0.258)	(0.257)
Primary Insurer - GEICO	1.382^{***}	1.389^{***}	1.314^{***}	1.383^{***}
	(0.164)	(0.163)	(0.119)	(0.164)
Primary Insurer - Hartford	2.036^{***}	2.026^{***}	1.607^{***}	2.029^{***}
	(0.426)	(0.428)	(0.460)	(0.426)
Primary Insurer - Liberty Mutual	-0.807^{**}	-0.808^{**}	-1.152^{**}	-0.804^{**}
	(0.317)	(0.319)	(0.517)	(0.318)
Primary Insurer - MetLife	1.314^{***}	1.289^{***}	3.029^{***}	1.305^{***}
	(0.406)	(0.398)	(0.320)	(0.403)
Primary Insurer - Nationwide	1.764^{***}	1.775^{***}	1.987^{***}	1.764^{***}
	(0.320)	(0.320)	(0.247)	(0.321)
Primary Insurer - Progressive	2.668^{***}	2.647^{***}	0.629^{**}	2.664^{***}
	(0.246)	(0.247)	(0.285)	(0.247)
Primary Insurer - State Farm	1.246^{***}	1.246^{***}	2.074^{***}	1.246^{***}
	(0.146)	(0.145)	(0.194)	(0.146)
Primary Insurer - Travelers	-0.418	-0.409	-0.581	-0.415
	(0.443)	(0.438)	(0.510)	(0.444)
Primary Insurer - USAA	1.087^{***}	1.077^{***}	0.289^{**}	1.084^{***}
	(0.149)	(0.151)	(0.114)	(0.149)
Own Zip Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	Yes	Yes	Yes
Within R-squared	0.977	0.977	0.993	0.977
Observations	149,613	149,613	103,168	148,888
Residual Std. Error	47.190	47.128	25.452	47.263
Note:	*p<0.1; **p<0.05; ***p<0.01			

This table presents the results from a diff-in-diff regression of annual auto insurance premiums (at the zip-code level) for all zip codes in the contiguous United States that legalized medicinal marijuana from 2015 - 2018 compared to zip codes that either expanded prior to 2015 or have not expanded yet. Standard errors, clustered at the State level, are in parenthesis.

3.2 Border Zip Analysis:

Our second approach relies on a combination of difference-in-differences and a geographic discontinuity. Unlike recreational marijuana, you have to physically live in the state to qualify to purchase medical marijuana. This creates a hard discontinuity at the state border which we exploit through paired zip codes across borders where one state legalizes and the other does not. This geographic identification approach has precedent, though with counties. Gowrisankaran and Krainer (2011) examines ATM surcharges using differing laws in Minnesota and Iowa; Dube et al. (2010) uses it to examine minimum wage effects on job growth; and Baggio et al. (2018) examine the effect of medical marijuana on alcohol demand. In our analysis, we follow the methodology of Dube et al. (2010), estimating

$$y_{zpt} = \beta_1 Medical\_Marijuana_{st} + x'_{zt}\beta_2 + Own\_Zip_z + Zip\_Pair_p + Year_t + \epsilon_{zpt} \quad (5)$$

$$y_{zpt} = \beta_1 Registered\_Patients_{st} + x'_{zt}\beta_2 + Own\_Zip_z + Zip\_Pair_p + Year_t + \epsilon_{zpt} \quad (6)$$

$$\begin{aligned} y_{zpt} &= \beta_1 Medical\_Marijuana_{st} + \beta_2 Medical\_Marijuana_{st} : DUI_{z(t^*-1)} + x'_{zt}\beta_3 \\ &+ Own\_Zip_z + Zip\_Pair_p + Year_t + \epsilon_{zpt} \end{aligned} \quad (7)$$

$$\begin{aligned} y_{zpt} &= \beta_1 Medical\_Marijuana_{st} + \beta_2 Medical\_Marijuana_{st} : Smoking_s + x'_{zt}\beta_3 \\ &+ Own\_Zip_z + Zip\_Pair_p + Year_t + \epsilon_{zpt} \end{aligned} \quad (8)$$

Where y_{zpt} is the average annual auto insurance premium for zip code z, in zip code pair p, and year t; x_{zt} is a vector of zip-code level controls (inclusive of an intercept); Zip_Pair_p is a vector of pair-specific fixed effects; and the rest of the variables are the same as Equations (1)-(4).

The standard errors for Equations (5) - (8) are more complicated. For our sample of near border zip-pairs, a single zip code may be in multiple pairs along a border. This induces a mechanical correlation across zip-pairs along the same border segment.[17] To account for all of these sources of residual correlation, the standard errors for Equations (5) - (8) are multi-way clustered by both state and border segment.

[17] A border segment is a state-pair specific border, such as the Pennsylvania - New York border.

The results of this estimation are presented in Table 6. The four columns of Table 6 are separated in the same manner as Table 5 described above. We find qualitatively similar (though slightly muted) results for the binary and continuous treatment models. We are unable to distinguish any differential effects from DUI-heavy areas or smoking states.

Table 6: Border Zips Diff-in-Diff

	Dependent variable:			
	Annual Premiums (1)	Annual Premiums (2)	Annual Premiums (3)	Annual Premiums (4)
Medical Marijuana Legalization	−5.207*		−0.941	
	(3.026)		(1.866)	
ln(Number Registered)		−0.492*		
		(0.286)		
Medical Marijuana Legalization : DUI_{t*-1}			−39.319	
			(89.089)	
Medical Marijuana Legalization : Smoking Allowed				−6.176
				(3.996)
Medical Marijuana Legalization : Smoking Not Allowed				−3.410
				(2.355)
Median Age	1.776***	1.776***	1.080**	1.837***
	(0.606)	(0.605)	(0.479)	(0.625)
Population with Bachelor's Degree	−0.029	−0.043	−0.236	−0.039
	(0.434)	(0.435)	(0.275)	(0.426)
Unemployment	−0.783	−0.794	−0.678	−0.787
	(0.666)	(0.680)	(0.712)	(0.666)
Population Density (#/sq. mi.)	0.013	0.014	−0.067	0.013
	(0.049)	(0.049)	(0.046)	(0.049)
Median Household Income	0.001***	0.001***	0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Drivers Under 25 on Policy	−0.062*	−0.063*	−0.046	−0.063*
	(0.033)	(0.034)	(0.029)	(0.033)
Number Insured	0.518***	0.518***	0.768***	0.516***
	(0.116)	(0.116)	(0.072)	(0.117)
Primary Insurer - AAA	−0.177	−0.177	2.282***	−0.174
	(0.167)	(0.167)	(0.512)	(0.168)
Primary Insurer - Allstate	1.635***	1.636***	0.441	1.635***
	(0.306)	(0.307)	(0.304)	(0.306)
Primary Insurer - American Family	0.871*	0.872*	0.598	0.863*
	(0.454)	(0.453)	(0.436)	(0.455)
Primary Insurer - Farm Bureau	4.679***	4.672***	2.179***	4.676***
	(0.680)	(0.680)	(0.436)	(0.680)
Primary Insurer - Farmers	−3.408***	−3.412***	0.226	−3.405***
	(0.549)	(0.549)	(0.917)	(0.548)
Primary Insurer - GEICO	2.695***	2.694***	1.492***	2.696***
	(0.133)	(0.132)	(0.216)	(0.133)
Primary Insurer - Hartford	1.236**	1.241**	1.553***	1.237**
	(0.568)	(0.568)	(0.563)	(0.567)
Primary Insurer - Liberty Mutual	0.405*	0.406*	0.901***	0.406*
	(0.240)	(0.239)	(0.214)	(0.238)
Primary Insurer - MetLife	−0.731	−0.734	2.852***	−0.721
	(0.520)	(0.519)	(0.464)	(0.522)
Primary Insurer - Nationwide	2.426***	2.421***	2.536***	2.428***
	(0.390)	(0.388)	(0.566)	(0.390)
Primary Insurer - Progressive	−0.248	−0.246	1.265**	−0.245
	(0.176)	(0.176)	(0.553)	(0.176)
Primary Insurer - State Farm	1.360***	1.360***	1.160***	1.359***
	(0.136)	(0.135)	(0.185)	(0.135)
Primary Insurer - Travelers	−0.222	−0.227	0.594**	−0.221
	(0.440)	(0.440)	(0.291)	(0.439)
Primary Insurer - USAA	−0.402	−0.402	0.192	−0.403
	(0.272)	(0.272)	(0.202)	(0.272)
Own Zip Effects?	Yes	Yes	Yes	Yes
Year Effects?	Yes	Yes	Yes	Yes
Pair Effects?	Yes	Yes	Yes	Yes
Within R-squared	0.976	0.976	0.991	0.976
Observations	58,705	58,705	41,156	58,705
Residual Std. Error	27.072	27.073	15.438	27.068

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

This table presents the results from a diff-in-diff regression of annual auto insurance premiums (at the zip-code level) for all border zip codes in the contiguous United States in states that legalized medicinal marijuana from 2015 - 2018 paired with zip codes in bordering states. Standard errors, clustered at the State and border segment level, are in parenthesis.

3.3 Dispensary Analysis:

Our third specification is a heterogeneous treatment effect model defining zip codes near a dispensary in states that legalize from 2015 - 2018 as our "heavily-treated" group, zip codes in states that legalize from 2015 - 2018, but are far from dispensaries as our treated group, and zip codes in states that have not expanded as our control group. If our story is correct, and our results are not driven by some other state-level phenomenon correlated with marijuana legalization, then the effect should be stronger near dispensaries. Specifically, we estimate

$$
\begin{aligned}
y_{zt} &= \beta_1 Medical\_Marijuana_{st} + \beta_2 Medical\_Marijuana_{st} : Dispensary_{tz} + x'_{zt}\beta_2 \\
&+ Own\_Zip_z + Year_t + \epsilon_{zt} \qquad (9) \\
y_{zt} &= \beta_1 Registered\_Patients_{st} + \beta_2 Registered\_Patients_{st} : Dispensary_{tz} + x'_{zt}\beta_2 \\
&+ Own\_Zip_z + Year_t + \epsilon_{zt} \qquad (10)
\end{aligned}
$$

Where $Dispensary_{zt}$ is a binary indicator for if the zip code is within 25 miles from a zip code where a dispensary opens and the other variables are the same as described above.

The results of this estimation are presented in Table 7. The two columns of Table 7 are separated by the use of a binary versus a continuous treatment variable. In both cases, we find that the effect of legalization is largely driven by zip codes near dispensary openings, providing further evidence that our effect is driven only by medical marijuana legalization.

Table 7: Dispensary Treatment Diff-in-Diff

	Dependent variable:	
	Annual Premiums	Annual Premiums
	(1)	(2)
Medical Marijuana Legalization	-4.419	
	(3.448)	
Medical Marijuana Legalization : Dispensary	-11.570^{*}	
	(6.098)	
ln(Number Registered)		-0.610
		(0.417)
ln(Number Registered) : Dispensary		-1.859^{*}
		(1.022)
Median Age	0.688^{**}	0.701^{**}
	(0.319)	(0.315)
Population with Bachelor's Degree	-0.016	-0.003
	(0.149)	(0.149)
Unemployment	-0.044	-0.040
	(0.143)	(0.141)
Population Density (#/sq. mi.)	0.007^{***}	0.007^{***}
	(0.003)	(0.003)
Median Household Income	0.001^{***}	0.001^{***}
	(0.000)	(0.000)
Drivers Under 25 on Policy	-0.146^{***}	-0.143^{***}
	(0.034)	(0.036)
Number Insured	0.439^{***}	0.442^{***}
	(0.039)	(0.038)
Primary Insurer - AAA	0.117	0.120
	(0.078)	(0.078)
Primary Insurer - Allstate	0.581^{***}	0.574^{***}
	(0.178)	(0.176)
Primary Insurer - American Family	-1.158^{**}	-1.156^{***}
	(0.451)	(0.443)
Primary Insurer - Farm Bureau	1.644^{***}	1.635^{***}
	(0.504)	(0.504)
Primary Insurer - Farmers	-0.184	-0.156
	(0.689)	(0.680)
Primary Insurer - GEICO	1.779^{***}	1.772^{***}
	(0.196)	(0.195)
Primary Insurer - Hartford	1.861^{***}	1.876^{***}
	(0.306)	(0.304)
Primary Insurer - Liberty Mutual	-0.266	-0.255
	(0.293)	(0.293)
Primary Insurer - MetLife	0.999^{*}	0.991^{*}
	(0.561)	(0.557)
Primary Insurer - Nationwide	2.199^{***}	2.208^{***}
	(0.171)	(0.174)
Primary Insurer - Progressive	1.611^{***}	1.605^{***}
	(0.345)	(0.344)
Primary Insurer - State Farm	1.170^{***}	1.168^{***}
	(0.130)	(0.129)
Primary Insurer - Travelers	-0.617	-0.607
	(0.517)	(0.518)
Primary Insurer - USAA	0.746^{***}	0.749^{***}
	(0.278)	(0.278)
Own Zip Effects?	Yes	Yes
Year Effects?	Yes	Yes
Within R-squared	0.979	0.979
Observations	118,114	118,114
Residual Std. Error	40.019	39.900
Note:	*p<0.1; **p<0.05; ***p<0.01	

This table presents the results from a diff-in-diff regression of annual auto insurance premiums (at the zip-code level) for all zip codes in the contiguous United States in states that legalized medicinal marijuana from 2015 - 2018 versus those who have not legalized. Dispensary is a binary variable for zip codes located within 25 miles of a zip code where a dispensary has opened. Standard errors, clustered at the State level, are in parenthesis.

3.4 Firm-level Analysis:

Finally, to ensure there are no demand-side effects confounding our analysis, we turn to our firm-state level data and estimate:

$$Y_{lfst} = \beta_1 Medical\_Marijuana_{st} + X'_{lfst}\beta_2 + Firm_f + State_s + Year_t + State_s : t + \epsilon_{lfst} \quad (11)$$

Where Y_{lfst} is the either the *Loss Ratio*, *Losses* (*logged*), or *Premiums* (*logged*) for policies in line l, written by firm f, in state s, and year t; $Medical\_Marijuana_{st}$ is the binary treatment variable for when state s legalizes medical marijuana; X_{lfst} is a vector of line, firm, and state level controls (inclusive of an intercept); $Firm_f$ is a vector of firm fixed effects; $State_s$ is a vector of state fixed effects; $Year_t$ is a vector of year fixed effects; $State_s : t$ are state-specific time trends; and ϵ_{lfst} is the mean-zero error term.

The results for this analysis are presented in Table 8. The first column shows the effect of legalizing medical marijuana on the *Loss Ratio*. The effect is not statistically different from zero, but absence of evidence is not evidence of absence. However, the point estimate is negative which, if true, would imply that our estimate is conservative. The second and third columns of Table 8 show the effect of legalizing medical marijuana on *Premiums* and *Losses*, respectively. While the point estimates for both are negative, which is congruent with our earlier results, the estimates are too noisy to distinguish from zero.

Unlike the prior models, for this one we do have enough data to check for pre-trends. The results of this check are presented in Figure 2. With the inclusion of state trends, our model does pass the parallel pre-trends check. Additionally, it appears that there is no lagged treatment effect to worry about.

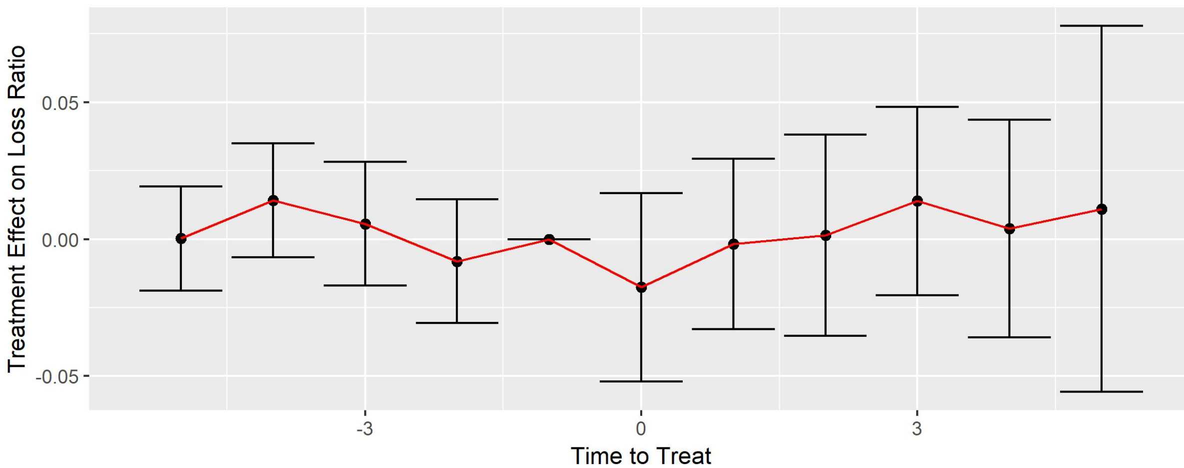
Table 8

	Dependent variable:		
	Loss Ratio	Premiums	Losses
	(1)	(2)	(3)
Medical Marijuana Legalization	−0.005	−0.064	−0.072
	(0.015)	(0.045)	(0.064)
Market Share			6.924***
			(1.134)
Stock	−0.052***	−0.673***	−0.815***
	(0.014)	(0.149)	(0.164)
Group	0.021**	−0.012	0.032
	(0.009)	(0.079)	(0.083)
Direct	0.002	0.200***	0.189***
	(0.004)	(0.040)	(0.041)
Log(Assets)	0.006***	0.336***	0.353***
	(0.002)	(0.016)	(0.019)
Num. States	−0.002***	0.019***	0.013***
	(0.000)	(0.003)	(0.003)
Log(Youth Ratio)	−0.016*	−0.002	−0.038
	(0.008)	(0.031)	(0.036)
Strict	−0.016	0.012	−0.028
	(0.010)	(0.029)	(0.027)
Log(Num. Drivers)	−0.040	0.066	−0.039
	(0.039)	(0.173)	(0.178)
Noneconomic Damage Caps	−0.004	0.048	0.037
	(0.007)	(0.031)	(0.034)
Punative Damage Caps	−0.002	0.016	0.010
	(0.006)	(0.023)	(0.027)
Collateral Source Reform	0.007	0.006	0.022
	(0.009)	(0.037)	(0.035)
Joint and Several Liability Reform	0.023***	−0.043	0.009
	(0.007)	(0.045)	(0.047)
Log(Median Income)	−0.024	0.783	0.632
	(0.211)	(0.791)	(0.834)
Log(State Gas Tax)	0.009	−0.062	−0.038
	(0.013)	(0.066)	(0.072)
Unemployment Rate	−0.009***	0.020**	0.001
	(0.003)	(0.009)	(0.011)
Per Capita Personal Income	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Drug Per Se Law	0.006	0.001	0.015
	(0.007)	(0.022)	(0.028)
Secondary Seatbelt Law	0.002	0.084**	0.102*
	(0.021)	(0.036)	(0.052)
Texting Ban	−0.007	−0.002	−0.006
	(0.007)	(0.029)	(0.030)
Legal Alcohol Limit .08	−0.008	−0.004	−0.027
	(0.006)	(0.025)	(0.028)
Speed Limit 70 Plus	−0.010*	0.009	−0.012
	(0.005)	(0.022)	(0.022)
Zero Tolerance Laws	−0.002	−0.060***	−0.058***
	(0.007)	(0.022)	(0.022)
Admin License Revocation	0.003	0.008	0.006
	(0.006)	(0.059)	(0.064)
Graduated Drivers Licensing	−0.002	−0.038	−0.053**
	(0.007)	(0.023)	(0.026)
Per Gallon Beer	−0.008	0.336**	0.421**
	(0.021)	(0.161)	(0.182)
Other Priv. Auto Liab. Line	−0.093***	1.460***	1.480***
	(0.016)	(0.180)	(0.201)
Physical Damage Line	−0.181***	1.241***	1.129***
	(0.019)	(0.173)	(0.195)
Rating Controls?	Yes	Yes	Yes
Firm-State Effects?	Yes	Yes	Yes
Year Effects?	Yes	Yes	Yes
State-Trends?	Yes	Yes	Yes
Observations	370,999	370,999	370,999
R^2	0.105	0.512	0.494
Residual Std. Error	0.343	1.873	2.030

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

This table represents multiple treatment diff-in-diff regressions for the impact of legalizing medical marijuana. Column (1) is the effect on the Loss Ratio . Column (2) is the effect on Premiums (logged). Column (3) is the effect on Losses (logged). All columns include ratings dummies, firm-state fixed effects, and year effects. Standard errors (in parentheses) are clustered at the state level.

Figure 2: Parallel Trends Check



4 Conclusions:

Our results indicate that the legalization and use of medical marijuana has a positive impact on auto safety, especially in areas that have higher levels of drunk driving. Other literature on this topic (which largely finds null or negative results) has been hampered by the reliance on data which only reports fatal accidents. Through our use of the direct effect on auto insurance prices, we are able to complete a more comprehensive picture. While we are unable to identify a separate effect for states which allow smoking as a method of consumption, there are other differences in laws (such as the allowance for home growth) that could be exploited for future research. Additionally, the question of who is “driving” the effect (those using marijuana legally vs illicitly) is another excellent avenue for future research.

Our results indicate the increase in auto safety is due, at least partially, to a decrease in driving while under the influence of alcohol. However, we caution against interpreting this a direct evidence of an alcohol/marijuana substitution effect. Another plausible explanation is that legalizing medical marijuana does not change the quantity of alcohol consumption but instead changes its location. Bar-equivalents do not typically exist for medical marijuana and thus joint consumption is likely to take place in the home. We do not examine recreational laws because our identification techniques do not apply, and would advise policy-makers against extending our results on medical towards recreational use since the habits of consumption are very different under the two regimes.

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