REALTY OF LEGALIZATION

Marijuana legalization impact on rental prices in the US

GROUP 03

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Abstract

This project examines the impact of marijuana legalization in the states of Colorado and Washington in 2012 and establishes a causal relationship between the rental prices and the legalization in these states. The modelling adopts a difference in difference approach to see the impact on the cities of the affected states vs. the non-affected states. Comparison is done with similar cities using propensity score matching to identify similar cities. The results show an incremental increase in the rental prices in Colorado and Washington compared to other states. The results hold true for multiple analysis (matched states, unmatched states and neighboring states) and placebo test is done to check the robustness of the model. Areas for future work , recmmendations for the policy makers are discussed on the basis of the results.

Introduction and Background

There had been strong laws prohibiting the non-medicinal use of marijuana in the US since 1930. However, in 2012, Colorado (55% supporters) and Washington (56% supporters) became the first states in the US to legalize marijuana use for recreational purpose. The initiative authorized individuals of age 21 and above to grow up to six plants and to purchase, possess up to one ounce of marijuana [1,3]. Legalization of marijuana has been a hot topic of debate for its impact on the society, key discussion points around legalization being the impact on state revenues, crime rates, health, traffic accidents, teen marijuana usage etc. This became more important as other states went ahead to follow the same suit as Colorado and Washington. The figure below shows the recreational marijuana legalized states comparison for 2012 vs. 2016. In 2015, the marijuana sales for Colorado were close to $1B, in 2016 the tax collection for Colorado and Washington was $140M and $270M respectively. The studies and press releases after the legalization in 2012 provide evidence of state revenue increase, while crime, suicide rate, health etc. have not shown any spike or dip. This study aims to find if there has been any latent impact of legalization that missed the policy makers' eyes but has a profound impact on people's lives. The study focusses on the impact of marijuana legalization on the property rental prices in the states of Colorado and Washington. The project is centred around the causal analysis of legalization on rental prices based on Difference-in-difference (DiD) approach. Colorado and Washington states in the US are investigated and compared to the states that do not approve marijuana for recreational purpose, to evaluate its impact on property rental movement.

The analysis is aimed to provide a holistic view on the impact of legalization to the policy makers, for them to make an informed decision. This acts as an important aspect to consider before framing the law, provides insight in deciding whether the similar law should be passed in their states and measures to be taken to combat the potential effects that legalization brings. However, this is a broad issue that impacts every American citizen voting for the law as this latent factor directly impacts their cost of living.

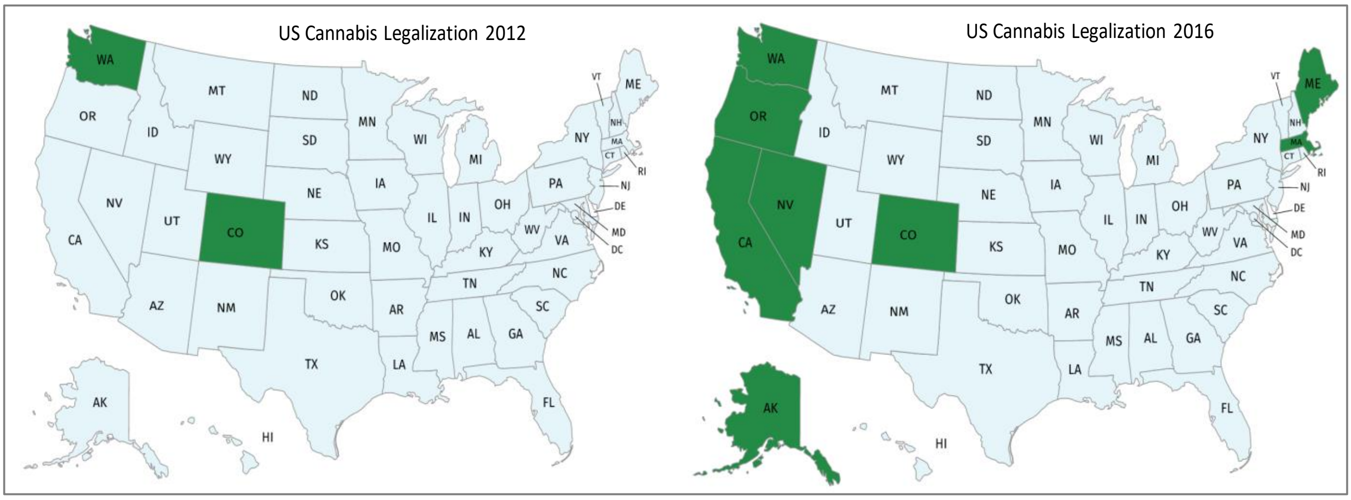


Figure 1: Recreational marijuana legalization comparison between 2012 and 2016

Literature and Novelty

There have been studies and articles around the impact of legalization on state tax revenues, health of citizens, crimes, road accidents under influence etc. Most of the studies, press reports are centred on the economic impact of legalization, the tax boost to the economy [2]. The studies are mostly based on the indicative trends for the afore-mentioned subjects before and after the legalization, there is not much literature available with robust statistical analysis.

Some press articles mention the impact of legalization on the day-to-day lives, which gives the direction for this study. The effect variable i.e. rental prices and the analysis method using a difference-in-difference approach is something that has not been worked upon before and hence makes the approach different. Furthermore, the legalization can be considered as an exogenous shock for the property rentals and hence takes care of reverse causality, thereby framework for the causal analysis is robust.

Data Collection and Processing

Finding appropriate data sources, cleaning and transformation is the key element of any study. The major data classes for this study are crime data, demographics and macroeconomic factors, property data. Below table (Table 1) summarizes the data source, granularity, and time period.

Data	Data group	Source	Granularity	Time-period
Dependent Variable	Median rent	US Census Bureau	City - Year	2011-2014
Control Variables	Schools	National Center for Education Statistics	City - Year	2011-2014
	Crime	U.S. Department of Justice - Federal Bureau of Investigation		
	GDP	Internal Revenue Service		
	Income	US Census Bureau		
	Housing information			
	Population			
	Unemployment			

Table 1: Data sources and description

Data manipulation

The data is collected at zip code level except crime data that can only be collected at city level. Therefore, except for crime, all other data was rolled up from a ZIP code level using USPS ZIP-city mapping. The analysis is conducted at city level.

Data Processing

After rolling up all data to city-level, further data processing is conducted as below:

1. Import crime, demographic, school and housing data at city level in R

2. Remove NA values in the data if any
3. Filter out cities that do not have 4-years of crime, demographic, school and housing data
4. Identify Colorado and Washington states as treatment group and the other states as control groups
5. Converting the following variables as percentages
    a. Violent crime and property crime
    b. Occupied/ Vacant housing units
    c. Housing units with/ without fuels and with/ without various types of energy
    d. Housing units with/ without kitchens and telephone
    e. Gender and ethnicity
6. Adding a flag to identify a post period

For some housing and population variables, the values are distributed over buckets (e.g. population 10-14 years, 15-19 years and so on). For such variables, the values are first rolled up to city levels and then based on the cumulative addition of the buckets (starting from lowest to highest), the median value is selected. This is done under the assumption that values inside the buckets are uniformly distributed.

Independent Variables Selection

There are two types of data used for the analysis – median rent as the dependent variable and control variables. Table 2 below includes the summarized description and hypothesis of why the following variables are selected as independent variables for the model.

Data Usage

The variables stated in section of Independent Variable Selection are used for panel regression model, principle component analysis and placebo test since yearly data from 2011 to 2014 is available.

Demographic information has only been used in propensity score matching. Since the census is only conducted after a certain amount of time, there is insufficient demographic information in the post period.

Alaska, Hawaii and Puerto Rico are not included in the dataset since they are remote from the US continent.

Exploratory Data analysis

Before beginning with the causal analysis, some basic exploratory analysis was done that would help give a

Data	Data group	Variables	Description	Hypothesis
Dependent Variable	Median rent	median_gross_rent	Median monthly rent includes an estimate of utility costs	NA
Control Variables	Schools	number_of_schools	Number of schools in the city	The higher is number of schools could lead to a higer rent as families could choose to rent a house near the school
	Crime	Violent.crime	Violent crime rate (per 1000 people)	The higher is the violent crime rate, the lower is the rent
		Property.crime	Property crime rate (per 1000 people)	The higher is the property crime rate, the lower is the rent
	GDP	Adj_Gross_Income_tot	Total income generated by the city government in thousands	It gives an indication of GDP. The higher the number could mean a higher rent due to inflation
	Income	average_household_income	Average household income in a city	The higher the income could lead to a higher rent as people are affordable to spend more on the rent of the same house
		total.housing.units	Total number of housing units in the city	A higher number of total housing units could lead to a lower rent due to an increase in housing supply
		occupied.housing.units	Proportion of house that are occupied	The higher the proportion could lead to a higher rent because there are less available house in the rental market
		units.with.electricity	Proportion of house that are equipped with electricity	The higher is the proportion could lead to a higher rent due to availability of electricity
		units.without.fuel	Proportion of house that are not equipped with fuel	The higher is the proportion could lead to a lower rent due to unavailability of fuel supply
	Housing information	median_smoc_mortgage	SMOC is Selected Monthly Owner Costs which is about the cost of maintainence of the house. This variable captures the median SMOC for those houses which have been mortgaged	The higher the SMOC could lead to a lower rent if the tenant needs to bear the cost. The higher SMOC could also mean the house is needed to been repair more often
		median_smoc_no_mortgage	This variable captures the median SMOC for those houses which have not been mortgaged	
		median_age_building	The median age of the building	The higher is the age could lead to a lower rent since older building is relatively not attractive than those newer ones
		median_number_rooms	The median number of rooms in a housing unit	The higher is the number of rooms could lead to a higher rent
		median_occupancy_years	The median year of occupancy	The higher the number could lead to a higher rent as the turnover of the unit is lower
	Population	Population	the total population of a city	The higher is the population could lead to a higher rent as there could be more people chasing for the same unit of house
	Unemployment	percent_unemployment	Percetage of unemployment in the city	The higher percentage could lead to a lower rent as less people have steady income to pay for the rent

Table 2: Description of the data variables

directional idea about both, independent variable choice, and choice of inclusion of some of the control variables.

- *Population* – It was hypothesised that the massive economic opportunity would attract citizens from across the country into the states where legalization occurred. This hypothesis was explored, and directionality confirmed, as per the figure below. It was observed that the population growth rate sees a sudden spike post 2012, which is greater for CO and WA compared to the rest of the country

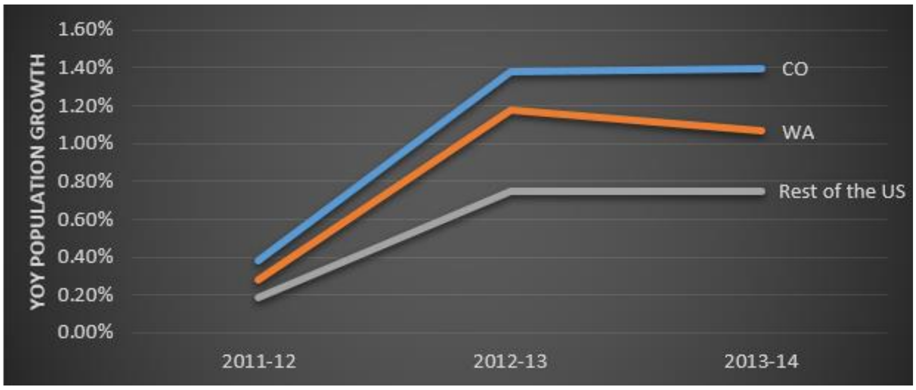


Figure 2: YoY population growth across CO, WA, and the rest of the US

- *Gross rent* – As evident from the figures below, there is a trend of house rent increase in the US. The average rent in Colorado and Washington, however, seem to be growing slightly faster than the rest of the country, post 2012. This hints that there might be a requirement for further investigation.

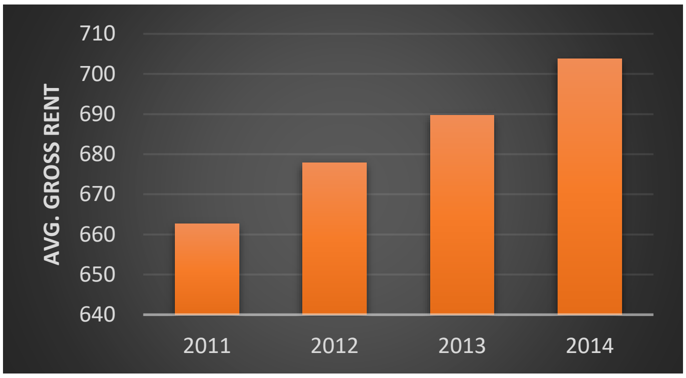


Figure 3: Average house rent across all states

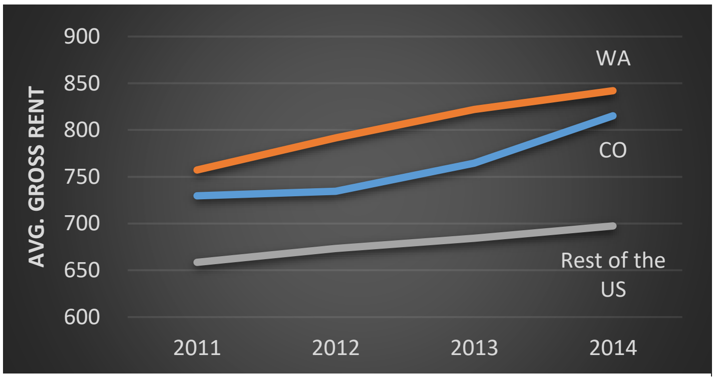


Figure 4: Average house rent across WA, CO and rest of the US

- *Value of owned property* – This was another consideration as point of study during the design phase of the project. However, based on the chart shown below, the hypothesis was that people preferred to rent houses in the states of Colorado and Washington post the legalization. This drove the growth in the average rent, while keeping the property value for owners almost constant.

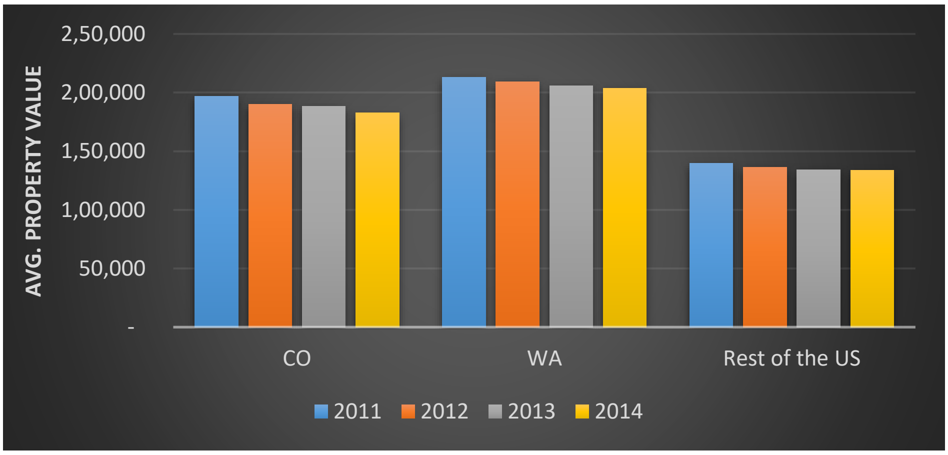


Figure 5: Trend in the property value across CO, WA, and the rest of the US

- *Crime rate* – The change in violent and property crime rate were studied in each state after the legalization in 2012. It was observed (as seen in the figure below) that, while the change in the violent crime rate seems consistent across the country, there is a variation in the property crime rate. Colorado, in fact, sees one of the highest increase in property crime post the legalization

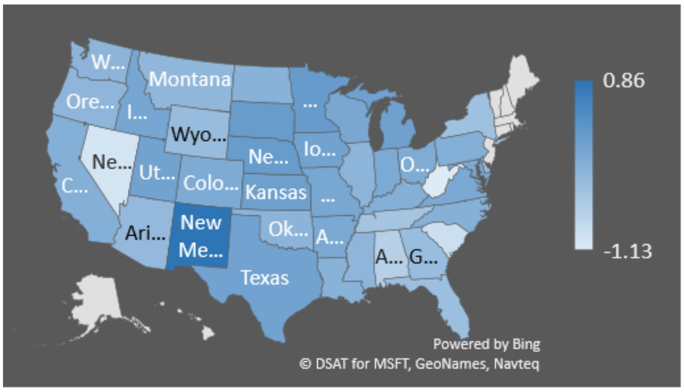


Figure 6: Change in violent crime rate post legalization

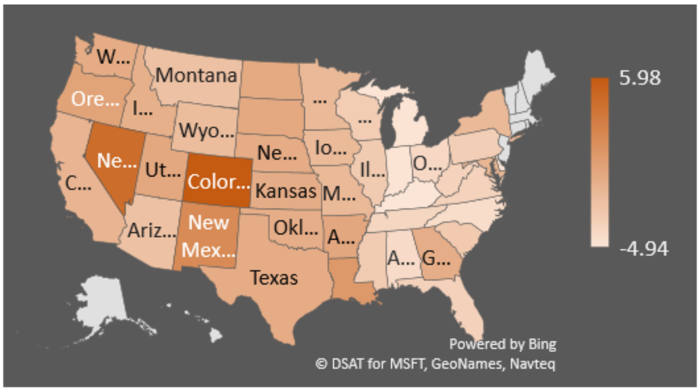


Figure 7: Change in property crime rate post legalization

Modelling, Analysis & Interpretation

To start with, a simple linear regression was run with only pre- and post-flag as the independent variable.

$$median\_gross\_rent \sim post\_flag$$

The result indicated the variable is significant and showed overall increase in rent across all states. However, the adjusted R-square is only 0.002, indicating this model cannot explain the variation of the dependent variable. Hence, panel linear models would be used for the data analysis.

```
Simple Linear Model Results
===============================================
                         Linear Model
                    ---------------------------
                              1
-----------------------------------------------
post_flag1                 26.447***
                            (4.502)

Constant                   670.299***
                            (3.183)

-----------------------------------------------
Observations                 14,140
R2                           0.002
Adjusted R2                  0.002
Residual Std. Error   267.668 (df = 14138)
F Statistic         34.510*** (df = 1; 14138)
===============================================
Note:               *p<0.1; **p<0.05; ***p<0.01
```

After considering the simple OLS model, a basic panel model is run to see the impact of legalization on the median gross rent over the year and city fixed effects. A difference in difference panel model is selected to see the impact of legalization on the cities in Colorado and Washington compared to the cities where recreational marijuana was prohibited till 2014 while controlling for the city and year fixed effects. This helps to eliminate any inherent difference between the cities and the coefficient for the interaction term provides the incremental increase in rental prices for the affected vs. non-affected cities (Figure 2). For the basic model, we do not include any demographic, crime or property controls.

$$\textbf{Median\_gross\_rent}_{it} = \alpha + \beta^*(\textbf{After Legalization}_t\textbf{*Affected Cities}_{it}) + \textbf{C}_i + \textbf{Y}_t$$

After legalization = Period after legalization i.e. 2013, 2014

Affected Cities = Treatment group i.e. cities in Colorado and Washington. A total of 167 cities

C_i = City-State fixed effects

Y_t = Year fixed effects

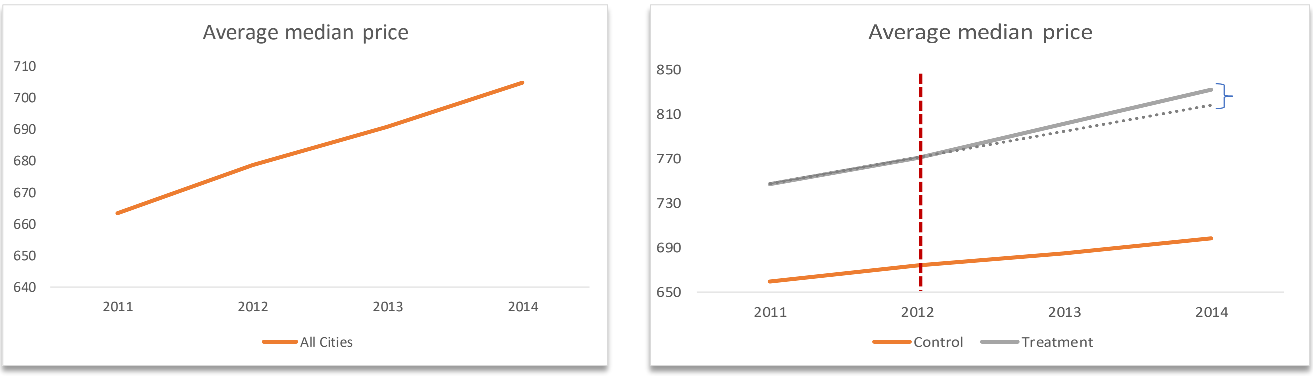


Figure 8: DiD implementation for median house rental price

The results show a general high rent trend for the affected cities while the interaction of the legalization effect is not within 95% significance level. However, a very low R-square of the model points to the missing attributes in the model.

In the next step, demographic, crime and property controls are added to improve the model explanatory prowess. This model is more robust in explaining the median gross rent, explaining 63% variance in the model.

$$\textbf{Median\_gross\_rent}_{it} = \alpha + \beta^*(\textbf{After Legalization}_t\textbf{*Affected Cities}_{it}) + \textbf{Controls} + \textbf{C}_i + \textbf{Y}_t$$

Controls include the violent, property crimes, adjusted gross income, average household income, property controls like median number of rooms, age of the building etc. The results for this model show a significant increase in the rent of the affected cities after legalization. The interaction coefficient (35) is an increase of an additional ~5% on the median gross rent of the affected cities. One possible hypothesis is the influx of population in Colorado and Washington after the legalization as people might have come to these cities to be a part of the booming industry. As the people who come to the city, would be first renting out places rather than buying the property at the first place, the increase in the rent as suggested by the model is intuitive. The model results for both the models are provided in the Table 3 below (detailed results are provided in the appendix)

Table 3: Baseline Panel Models

	1	2
Dependent Variable	**Median Gross rent**	
Affected Cities	93.031***	12.36
After legalization x Affected Cities	32.867	35.09**
Controls	NO	YES
FE	YES	YES
R-Squared	0.007	0.64

Before diving in further analysis, Hausman test for panel models is performed by running the random effect model and comparing the results with the fixed effects model. The low p-value provides the green signal to use the fixed effect model for further analysis.

Maintaining constant baseline bias using propensity score matching

One of the key assumptions of a Difference-in-Difference model is of a constant baseline bias between treatment and the control group. Up until now, the panel regressions being run show the results of using the entire treatment group and the entire control group. The model was further improved by ensuring that only the control group only consisted of cities that were similar to the treatment group, in terms of the variables being controlled for. This was done using a logistic propensity score matching, and choosing the most similar 5 cities from the control group, for each city in the treatment group. This was done with replacement, meaning the same city in the control group could be matched to multiple cities in the treatment group.

Variable	**Mean value in treatment group**	**Mean value in control group**	
		Matched sample	**Full Sample**
Adjusted GDP	14,73,088.485	14,59,383.222	10,32,945.047
Household income	67,000.328	66,212.351	62,871.873
Building age	37.179	37.479	41.058
Number of rooms	5.587	5.613	5.601
Years of occupancy	4.463	4.933	7.812
Total housing units	21,163.329	20,996.455	16,808.009
Number of schools	1.701	1.959	2.085
Occupancy rate	0.869	0.875	0.873
Unemployment rate	4.725	4.593	4.544
Population	32,842.246	36,133.050	28,987.353
Property crime rate	39.673	29.505	29.251
Violent crime rate	3.021	2.576	3.153

Table 4: Comparing the similarity of the treatment and control group pre- and post-PSM

As it can be seen, the PSM results in a more similar control group to the treatment group, which was further confirmed using a t-test. Now, using this group, the panel regression model was re-run, and results re-affirm the previous findings (as can be seen from the below table)

```
====================================================
                          Dependent variable:
                          --------------------------
                              median_gross_rent
----------------------------------------------------
post_flag1                         17.216***
                                    (5.675)

treat_flag1:post_flag1             31.881***
                                    (9.386)

----------------------------------------------------
Observations                         2,436
R2                                   0.068
Adjusted R2                          0.051
F Statistic                  7.389*** (df = 18; 1809)
====================================================
Note:                     *p<0.1; **p<0.05; ***p<0.01
```

Table 5: Regression results post propensity score matching

In the Next phase the analysis tries to deep dive to try and understand if there are any specific factors that influence the treatment effect.

Performing Principal Component Analysis

A principal component analysis is performed to help in dimension reduction as a large number of control variables such as housing characteristics, income information, crime statistics and unemployment rates are being used in the panel regression. At this stage of the analysis the aim is to deep dive and improve model outputs. The principal component analysis should help achieve the same.

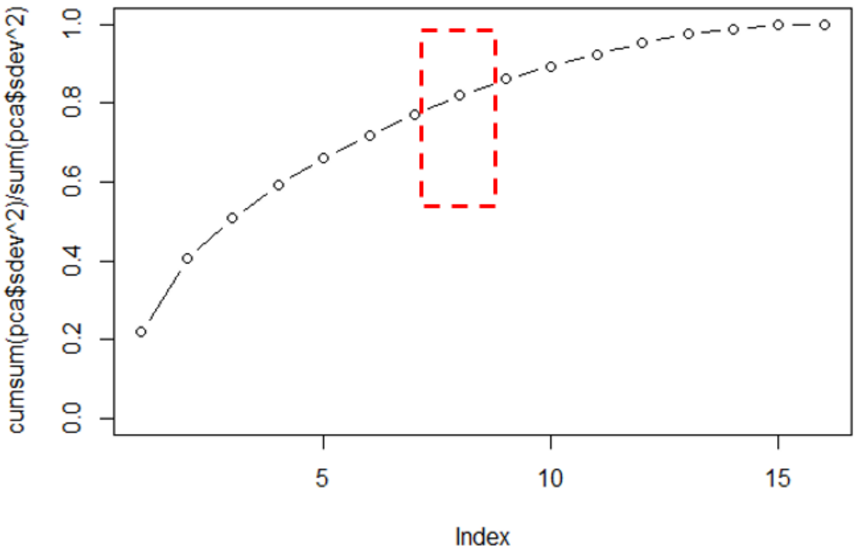


Figure 9: The principal component output suggests that **8 principal components** considered are able to explain **80% of the variance in the data**. The Y axis in the above figure represents % cumulative sum of standard deviation square.

Running Panel Regression with Principal Components

In the next step the fixed effect panel regression is re-run by including the 8 principal components on the matched dataset (Dataset after doing a propensity score matching on the treatment and control cities). The output is as follows:

Median_gross_rentit = α + β*(After Legalizationt*Affected Citiesit) + PC1+PC2+PC3+PC4+PC5+PC6+PC7+PC8+ Ci+ Yt

Panel Regression with Principal Components	
Dependant Variable	**Median Gross Rent**
Affected Cities	9.65
After Legalization * Affected Cities	**36.104***
Principal components	**YES**
R-Square	64%

The R-Square hasn't increased much and stands at 64% the treatment effect interaction term is still significant but the P value stands at 0.02 slightly higher than the base model, in which the P value was 0.01.

Clustering using the principal components

In the next step a clustering analysis is performed to understand the different types of cities and their distinguishing characteristics. These city characteristics that help define the clusters would be further used as moderators in the panel regression model to help understand how they influence the treatment effect.

The clustering was done on the treatment group to identify distinguishing characteristics. To come up with distinct clusters a principal component analysis was again performed. This time 12 principal components were identified that explain 80% of the variance in the data. More control variables for housing were added such as units using solar/coal/fuel etc. 3 clusters are formed using the elbow method- The elbow method looks at the percentage of variance explained as a function of the number of clusters. The number of clusters are chosen such that adding an additional cluster doesn't give much better modelling results.

In the next step, each of the 3 cluster characteristics were analysed. Characteristics such as population, income, crime rate and number of housing units help distinguish between the 3 clusters formed. The following were then used as moderators in the panel regression to identify the influence on the treatment effect.

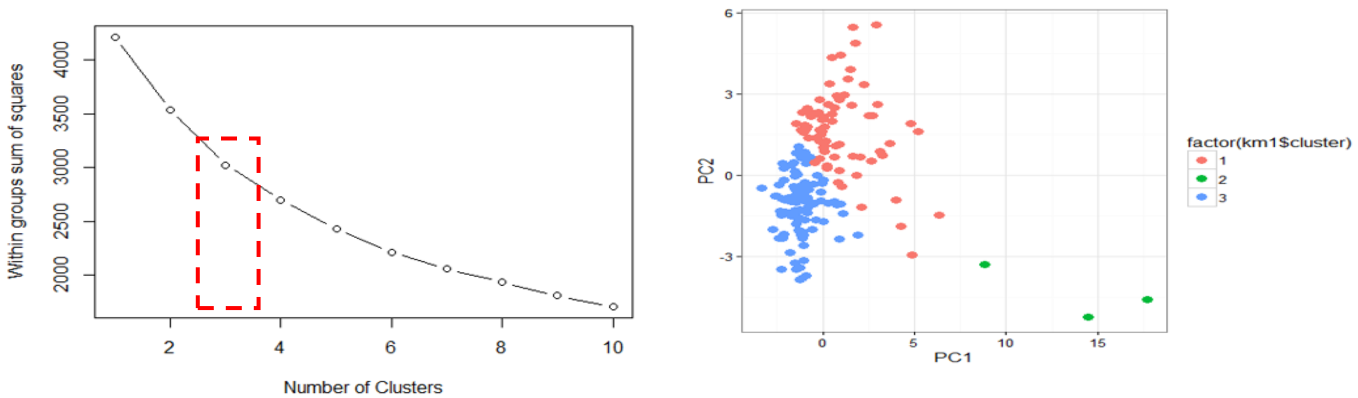
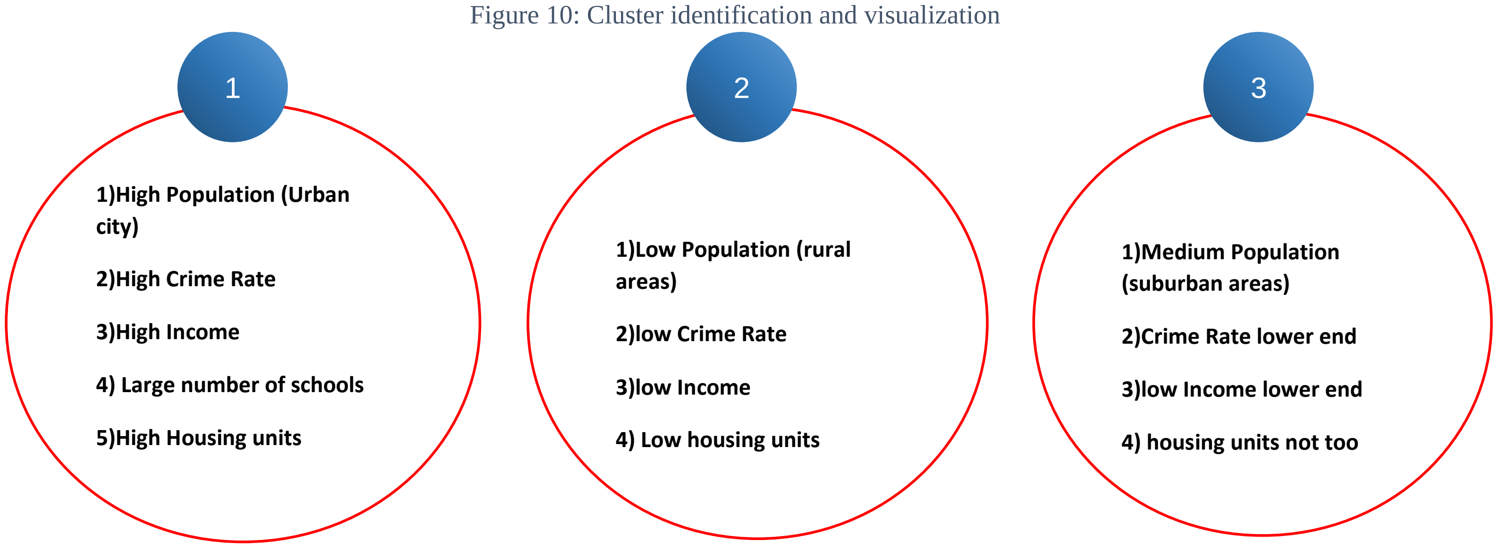


Figure 10: Cluster identification and visualization



The number of total housing units in the areas, which is also a proximate variable for housing density, and the median number of rooms in a house are moderators that indeed have an influence on the treatment effect.

Two panel regressions were run one with total housing units and the other with median number of rooms as moderators.

1)Median_gross_rentit = α + β*(After Legalizationt*Affected Citiesit*total housing units) + controls+ Ci+ Yt

2) Median_gross_rentit = α + β*(After Legalizationt*Affected Citiesit* median number of rooms) + controls+ Ci+ Yt

Output – Total housing unit moderator

Panel Regression with Moderators

Dependant Variable	Median Gross Rent Total housing units
After legalization	17**
Total Housing units	-0.024**
After Legalization * Affected Cities	33.99***
After Legalization * Affected Cities*Total Household units	-0.00049*
Controls	YES
R-Square	7%

The interaction term with Total housing units, post legalization period and affected cities has a negative coefficient and is significant, this suggests that places with low density of houses or less number of housing units, like suburban areas, have had a higher increase in rent post marijuana legalization.

Output – Median Number of Rooms moderator

Panel Regression with Moderators

Dependant Variable	Median Gross Rent Median Number of Rooms
After legalization	123**
After Legalization * Affected Cities*Median Number of Rooms	49***
Controls	YES
R-Square	8%

The interaction term with Median number of rooms, post legalization period and affected cities has a positive coefficient and is significant, this suggests that bigger houses with many rooms have a higher increase in rent post the marijuana legalization.

The above results show that bigger houses in the suburban areas, where marijuana is cultivated in green houses in the outskirts of the city, have had a higher increase in rent post the legalization. This could be a trickledown effect of the grow houses that are present in the area and has led to an increase in house rents.

Assessing the impact of rent in nearby cities

The idea here is that the rental prices in a city can be affected by the prices in nearby cities as well, forming a network effect. Thus, establishing the gross rent in nearby cities as a control variable could act as a model validation. To do so, city nearest to each of the cities in the universe was found, using the Haversine distance (as the crow flies)

$$
\begin{aligned}
d &= 2r \arcsin\left(\sqrt{\operatorname{hav}(\varphi_2 - \varphi_1) + \cos(\varphi_1)\cos(\varphi_2)\operatorname{hav}(\lambda_2 - \lambda_1)}\right) \\
&= 2r \arcsin\left(\sqrt{\sin^2\left(\frac{\varphi_2 - \varphi_1}{2}\right) + \cos(\varphi_1)\cos(\varphi_2)\sin^2\left(\frac{\lambda_2 - \lambda_1}{2}\right)}\right)
\end{aligned}
$$

Figure 11: Haversine distance formula (source: Wikipedia)

Once the nearest city was found, the rental price in that city was used as an additional control in the existing regression. The result validates our hypothesis regarding the network effect of rental price, while still showing a significantly higher increase in the treatment universe post legalization.

	Dependent variable:
	median_gross_rent
treat_flag1	-64.368
	(97.843)
post_flag1	11.961
	(10.188)
nearest_city_median_gross_rent	0.113***
	(0.042)
treat_flag1:post_flag1	31.690*
	(18.176)
Observations	920
R2	0.225
Adjusted R2	0.164
F Statistic	9.743*** (df = 20; 670)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 6: Regression results with the introduction of spatial regression

Impact on CO and WA relative to neighbouring states

Another question that arises is whether there is any spillover effect from the attraction to these 2 states, onto their neighbouring states. To check this, the control universe was confined individually to cities in the neighouring states for CO and WA individually.

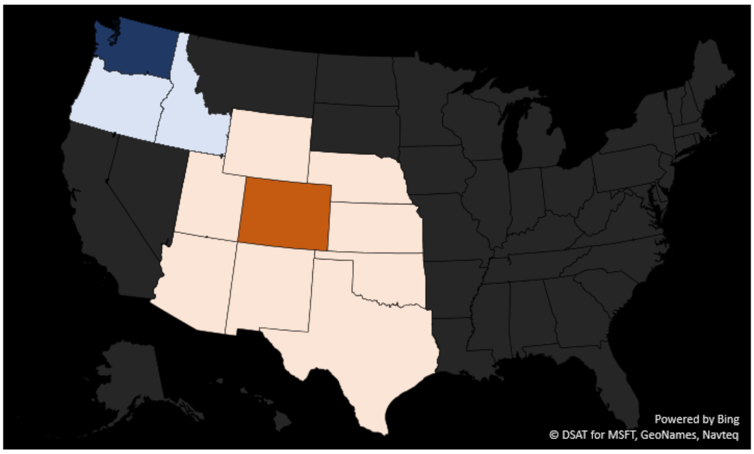


Figure 12: Map showing the respective treatment and control universe

The results from this analysis, is consistent with our earlier findings. This confirms that the increase is indeed seen only in CO and WA. However, it is a more prominent in CO (as per the significance and beta coefficient) than WA. So, this gives insight that CO saw a higher increase in the rent price relative to WA.

	Dependent variable:
	median_gross_rent
treat_flag1:post_flag1	33.040***
	(12.413)
Observations	3,364
R2	0.034
Adjusted R2	0.025
F Statistic	4.878*** (df = 18; 2505)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 7: Regression results for CO w.r.t neighbouring states

	Dependent variable:
	median_gross_rent
treat_flag1:post_flag1	27.523*
	(14.269)
Observations	832
R2	0.096
Adjusted R2	0.070
F Statistic	[illegible].595*** (df = 18; 606)
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 8: Regression results for WA w.r.t neighbouring states

Robustness of the model: Placebo test

Since the identification strategy uses a yearly data model, it is of utmost importance to ensure that the model is robust enough. To enable this, 2000 similar regression models were rerun. The difference however, was that in every one of those models, the assignment to treatment and control groups was random (similar to a double blind clinical trial), and post period definition was randomly chosen between the years 2012 and 2013. It can be seen from the above results, that more than 99% of the samples resulted in insignificant regression results. Even from the ones which did turn out of the significant (14 samples out of 2000), the effect is not similar to the measured effect earlier. This proves that the specificity of the treatment group and the year 2012 as the boundar, are essential in obtaining the results from the previous analysis. This would mean that the increase in rent is only seen in Colorado and Washington cities post 2012. A brief research also indicated that no other state laws were passed in these two states which would result in this observed increase post 2012, thereby ensuring model robustness.

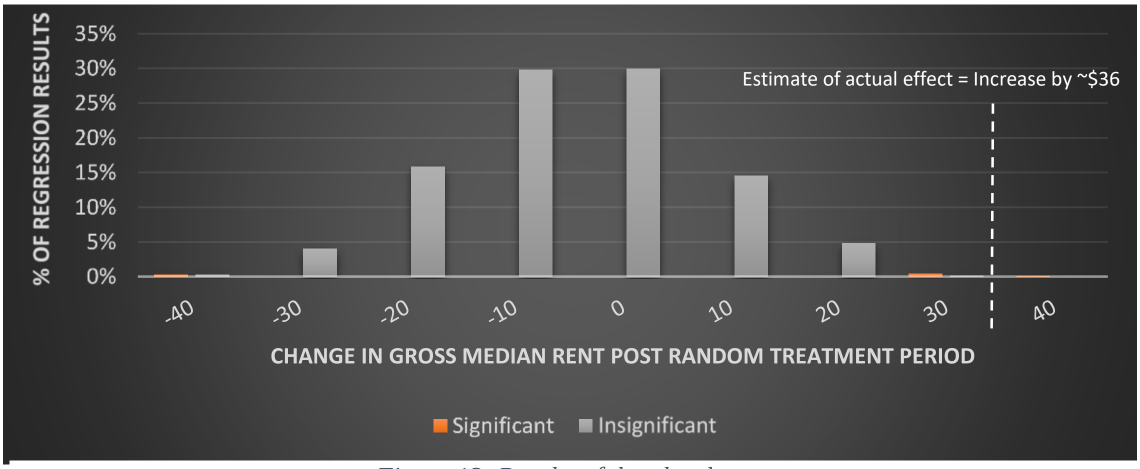


Figure 13: Results of the placebo test

Further improvements

Given the time constraint on the analysis performed, there is still room for improvement. Below mentioned are a few of possible enhancements possible in the analysis performed.

Regression discontinuity at the border of the affected states

Using the regression discontinuity as an additional identification strategy at the borders of CO and WA could further strengthen the results about the hypothesis that there was no spillover effect on the rental prices in neighbouring states. This can be achieved by finding the distance between the cities in CO and WA, and their neighbouring states' borders

Finding cities within CO and WA that saw a more prominent effect

Given that the legalization of Marijuana happened through a public vote, it would be interesting to see if the effect was focussed more in cities which had a higher percentage of voters for the motion. This can be done by using cities within CO and WA with a majority voting for the motion as treatment, while other cities in those states as controls. This would also require some additional data regarding the voting distrbution regarding the matter at a city level.

Verifying whether there was also an increase in commercial real estate rent

With the legalization of Marijuana, many firms opened up grow houses CO and WA. This could increase the demand, and therefore asking price, for the renting out commercial spaces. A similar analysis to the one conducted in this paper can be followed by using commercial real estate rental price as the dependent variable, and relevant control variables. Such data can be scraped from websites such as Craigslist, and other commercial real estate websites.

Conclusion

This paper is able to successfully show that the legalization of marijuana indeed has an effect on the rental prices in those states where the law has been passed. This analysis addresses one of the unintended effects of legaliation that would help policy makers and voters make an informed decision before marijuana is legalized in other parts of the world.

The panel regression results show that the treatment effect term is significant and that the house rents increase by about 5% in the treatment group when compared to the control group. In order to show a direct comparison a propensity score matching was done to find similar control cities for the treatment group and the result remained significant. The clustering approach helped identify moderators that would have an influential effect on the treatment , the analysis shows that house rents increased more in suburban areas with less housing density and where the houses have more number of rooms.

Robustness is one of the key aspects in a causal analysis and this paper implements a number of robustness tests to prove the causal effect. The treatment and control groups were randomly assigned and the post period time line was shifted between 2012 and 2013 , the results produced were insignifciant that shows that the specific treatment group and the year 2012 can only produce the desired results.

The analysis also controlled for rental prices in neighbouring states to show that the increase in rent in the treatment states was not a result of the trickle down effect of the change in rent prices in the neigbouring states. The control group was further restricted to only the neighbouring states and the treatment effect was still significant , this shows that the rent increase happened only in the treatment states where the policy was implemented.

References

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