**SHORT-TERM EFFECTS OF RECREATIONAL MARIJUANA LEGALIZATION ON CRIME**[*]

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**ABSTRACT.** New York became the 15th state to legalize marijuana for recreational use in 2021. With a growing share of the country legalizing cannabis, researchers and policymakers have studied the effects of its legalization on the economic and social characteristics of the states that have legalized marijuana. This analysis adds to the existing literature by exploring the implications of marijuana legalization for recreational use in New York State. Specifically, we analyze the impact of marijuana legalization on crime rates in New York City. We leverage New York Police Data and run a Two-Way Fixed Effects Difference-in-Differences model to estimate how crime rates changed after the passage of the law. We find that the legalization is associated with an increase in the number of arrests for some, but not all, violent crimes in precincts where marijuana arrests were high prior to the passing of the law. The increase in crime could be related to a reallocation of police resources to other crimes, but further analysis is necessary.

**JEL Codes**: K23; K42.
**Keywords**: Cannabis, recreational marijuana, crime, police resources.

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# 1 Introduction

In March 2021, New York became the 15th state to legalize the recreational use of cannabis when New York State Governor Andrew Cuomo signed the Marijuana Regulation and Taxation Act (MRTA) into law, which allows New Yorkers 21 years of age and older to possess up to three ounces of marijuana for recreational use. The implications of the legalization of Marijuana for recreational purposes across the United States have been explored extensively. Researchers have argued the effects of recreational marijuana include important benefits on the war on drugs and, in some cases, the reallocation of police resources to pursue other crimes.

In this paper, we build upon prior work by researchers and policymakers by studying the short-term effects of the legalization of recreational marijuana on crime rates in New York City by using detailed arrest data published by the New York Police Department (NYPD). Our results show that the legalization of recreational marijuana increased the number of arrests for murder crimes per hundred thousand inhabitants in precincts where marijuana possession arrests were high prior to the passing of the law. We argue that our findings are consistent with the literature reviewed. This would support that the reallocation of police resources, from chasing marijuana-related crimes to violent or property crimes, is a main consequence of marijuana legalization on crime.

The rest of this paper is organized as follows: Section 2 summarizes key literature from which this analysis has built upon. Section 3 describes the quasi-experiment we are exploiting to study the short-term effects of recreational marijuana legalization. Section 4 describes the database employed. Section 5 contains the econometric model, and Section 6 presents the model results. Finally, we write our conclusions and next steps to take to further the analysis in Section 7.

# 2 Theoretical framework

To motivate this study, we conducted a brief literature review on the effects of the legalization of marijuana for recreational use on crime rates. We rely mainly on what Dragone et al. (2019) have argued are the main mechanisms involved in how the legalization of marijuana influences crime. In summary, we group their findings into three factors: (1) the emergence of a legal market that deters the illegal one, (2) the increase of marijuana consumption and its effects on consumer behavior, and (3) the reallocation of police resources to go after other types of crimes.

The first factor was previously introduced by Becker (2014) and Becker and Murphy (2013). In their articles, the authors argue in favor of ending the "war on drugs", advocating for the benefits of legalizing the consumption and production of drugs. Their main argument states that the policy may have reduced the role for criminal gangs and small-time criminals in local cannabis markets. This would have been the result of an emergence of a legal market, which offers more safety and more reliable product quality via legitimate business, driving illegal sellers out of the market. Chimeli and Soares (2017) provide consistent evidence, finding that illegal markets are causally associated with crime.

The second factor states that crime rates are affected through an increase in recreational marijuana consumption. Studies indicate that cannabis use determines a variety of psychoactive effects, the most reported one being a state of relaxation and euphoria (Hall et al., 2001; Green et al., 2003). Thus, there is the potential that increased consumption of marijuana could reduce the likelihood of engaging in violent activities. Moreover, this effect is reinforced if cannabis is a substitute for violence-inducing substances such as alcohol, cocaine and amphetamines. Studies generally find that marijuana and alcohol are substitutes (Dragone et al., 2019; Anderson and Rees, 2014; Crost and Guerrero, 2012; DiNardo and Lemieux, 2001; Kelly and Rasul, 2014). Dragone et al. (2019) find this channel consistent with their findings, where they estimated a drop in rapes and a reduction in alcohol consumption associated with an increase in cannabis usage.

The third factor concerns the legalization of recreational marijuana influencing crime rates by inducing a reallocation of police efforts away from cannabis distributors and consumers and towards other types of offenses. This is a channel emphasized by Adda et al. (2014) in a study of the crime effects of depenalizing possession of small quantities of cannabis. Moreover, such reallocation of police effort may be reinforced by expectations, and therefore its effects on crime have arguably materialized before the actual opening of dispensaries and legal retail trade. The specification developed in this document is not enough to determine which of these mechanisms drive our results, and further exploration may shed light on this topic.

## 3 Police precincts by perpetration of marijuana related crimes: a quasi-experiment

Addressing the causal impact of legalizing marijuana possession for recreational use on crime posses a challenge. As a first challenge, we kept the scope of the study in a short-term scenario because of availability of data, since the event is slightly more than one year old to this date. Another challenge we faced consisted in dealing with finding groups by their exposure to the legalization event, in order to define both treatment and control groups in a reduced-form causal inference setting. Availability of data of arrests for a county or precinct level for other states similar to NY prevented us from using the typical federalist approach explored in other quasi-experiments found in the literature[1]. Nevertheless, we propose a quasi-experiment within NY borders where we distinguish groups that were more exposed than others to direct effects of the legalization of marijuana possession. We classify every police precinct in NYC according to the perpetration of marijuana possession arrests in 2019, a year previous to our experiment setting and define treatment and control groups.

We first calculated the number of arrests for marijuana possessions in 2019 for every 100,000 inhabitants in a given precinct. This crime rate exposes how important is marijuana in the precinct's arrest numbers: a higher crime rate for marijuana possession in a precinct means a larger presence of buyers and sellers of marijuana, as well as more police resources invested in chasing after these. We then proceed to evaluate the distribution of the proposed measure. A median of 53.81 marijuana possession arrests per 100,000 inhabitants in 2019 (or 4.48 in an average month), and a mean of 77.35 suggests the presence of extreme values at the right of the distribution. This probably identifies hot-spots where marijuana markets are concentrated. We finally define two groups using 2019 numbers: police precincts with marijuana arrests above the median and below the median, resulting in High and Low marijuana arrest precincts, respectively[2]. We would expect that change in legislation favor-

[1] In these quasi-experiment settings, changes in law at the state level allows to explore the impact of the law defining individuals within the state of law change as treatment and a neighboring or similar state with no law change as control.

[2] As a robustness check, Appendix A presents results using the same definition but applied to 2016-2018

ing recreational marijuana possession would impact differently these groups. Particularly, we expect that the precincts that destine more police resources to prosecute marijuana possession and that suffer from a higher presence of marijuana commercialization would be the most affected in terms of number of arrests. Figure 1 shows a map of all NYC police precincts by this classification.

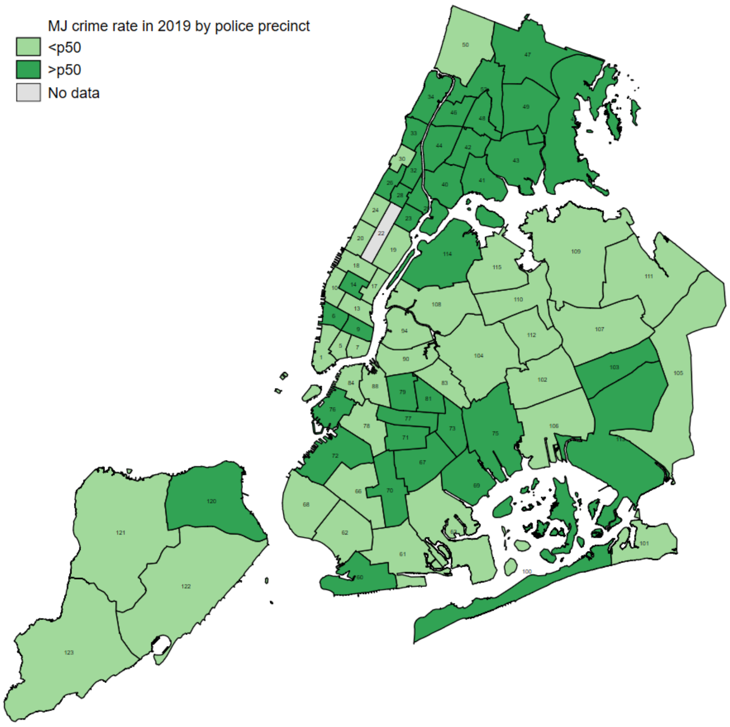



Figure 1: NYC Police Precincts, by Marijuana possession crime rates, 2019

Additionally, in order to ensure 2019 was an appropriate base year to reflect which precincts hold a higher presence of marijuana commercialization and police resources dedicated to chase after it, we define the same classification of precincts, but using information from the years 2016, 2017, and 2018. The results from applying the econometric model detailed in Section 5 using these new definitions for our treatment and control precincts can be found in Appendix A.

Regarding period of study, we would observe precincts' monthly crime rates between 2020 and 2021. The event of the study falls in the middle of this time period. Moreover, using this time period would be allow us to identify the dynamics of crime rates within the context of COVID-19 pandemic, which avoids comparing crime rates from periods previous to COVID-19 to crime rates during.

Having now defined high and low marijuana possession arrest precincts, and defining a period before (Pre) the date of the legislation passing, March 31st, and another period after (Post), both between 2020 and 2021. Table 1 reports the average crime rate for every type of crime explored in Section 4 by type of precinct (High vs Low) and by period of time (Pre vs Post). From these averages, we already can see a change in overall crime. High marijuana arrests precincts show overall crime rates significantly higher than low marijuana arrests precincts, while the same holds for all violent and property crime categories, except for Rape crimes. Likewise, post legislation period shows higher crimes rates than the pre

numbers.

legislation one, showing a increasing tendency on crime rates.

Table 1: Average crime rates per 100,000 inhabitants

| | All Crime | Violent | | | | | Property | | |
|---|---|---|---|---|---|---|---|---|---|
| | | All | Murder | Rape | Assault | Robbery | All | Theft | Burglary |
| High MJ2019 | | | | | | | | | |
| Pre | 214.151 | 136.671 | 11.419 | 3.843 | 97.427 | 23.983 | 77.480 | 60.884 | 16.596 |
| Post | 238.293 | 155.058 | 14.610 | 4.486 | 110.751 | 25.212 | 83.235 | 69.465 | 13.770 |
| Low MJ2019 | | | | | | | | | |
| Pre | 111.603 | 57.497 | 3.831 | 3.289 | 40.351 | 10.025 | 54.106 | 42.531 | 11.575 |
| Post | 126.735 | 68.339 | 5.141 | 4.469 | 48.609 | 10.120 | 58.396 | 49.035 | 9.361 |

Note: The table reports the average monthly crimes per 100,000 inhabitants in all NYC police precincts.
Source: NYPD Arrest Data 2020-2021.

# 4 Data

We employ the NYPD Arrest database in our analysis. This database includes all valid felony, misdemeanor, and violation arrests reported daily to the NYPD from 2006 to 2021. These are coded by date, offense description, police precinct description, and law code. Additionally, it provides demographic information about the offender such as sex, age group, and race.

We created our main database by merging the NYPD Arrest Data (Year To Date), which includes daily data for the year 2021, with the NYPD Arrest Data (Historic), which includes daily data from 2006 to 2020. We then proceeded to collect the address and zip code for each precinct on the database and merged it with the complete NYPD Arrest data from 2006 to 2021. Finally, we collected data on the population per zip code in New York City in the year 2020 from the U.S. census micro data and merged it with the aforementioned Arrests data by zip code.

For our analysis specifically, we are focused on crime data from January 2020 through December 2021 to compare how crime changed before and after the passing of the law in March 2021. We specifically decided to use this time horizon for the experiment to occur within the COVID-19 pandemic. This way we attempt to make COVID not be a relevant co-founding factor that will biased our results.

To measure the impact of the legalization of recreational use of marijuana on crime, we built standard indicators of crime rates for several types of crime. The definition of crime rate is given by the number of arrests per 100,000 inhabitants in each precinct. Crime rates are utilized as proxy of crime activity based on arrests in this study. This measure does not necessarily reflect whether less or more crimes are being committed, but rather whether the police are able to make the arrests or not for a given crime level. The main crime indicators we created are as follows:

1. Murder crime rate: This variable is the sum of arrests for crimes described as 'murder' by the NYPD classification per year-month for every 100,000 inhabitants in a given precinct.
2. Sex crime rate: This variable is the sum of arrests for crimes described as 'sex crime' by the NYPD classification per year-month for every 100,000 inhabitants in a given

precinct.

3. Assault crime Rate: This variable is the sum of arrests for crimes described as 'assault' by the NYPD classification per year-month for every 100,000 inhabitants in a given precinct.

4. Robbery crime rate: This variable is the sum of arrests for crimes described as 'robbery' by the NYPD classification per year-month for every 100,000 inhabitants in a given precinct.

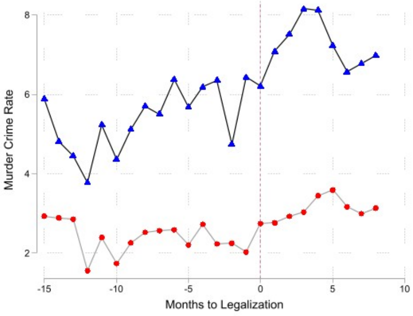
5. Violent crime rate: We defined Violent crimes as all the arrests made for the felonies classified as murder, sex crimes, assault, or robbery.

6. Burglary crime rate: This variable is the sum of arrests for crimes described as 'burglary' by the NYPD classification per year-month for every 100,000 inhabitants in a given precinct.

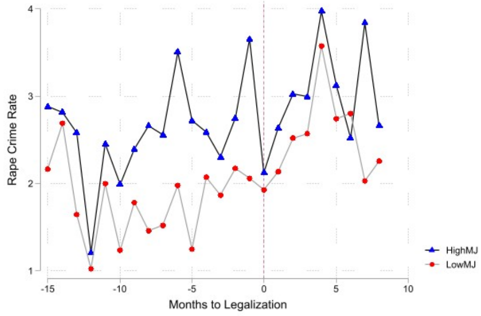
7. Theft crime rate: This variable is the sum of arrests for crimes described as 'theft' by the NYPD classification per year-month for every 100,000 inhabitants in a given precinct.

8. Property crime rate: this variable is the sum of arrests for all property crimes per year-month for every 100,000 inhabitants in a given precinct. We defined Property crimes as all the arrests for the felonies classified as burglary and theft.

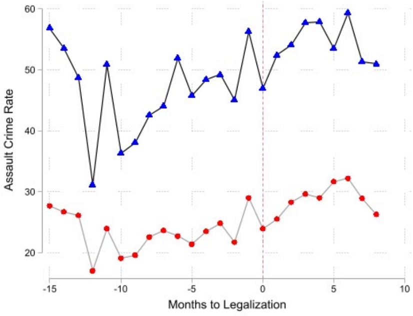
Figures 2 and 3 show the evolution of monthly trends for every crime rate between these two groups of precincts. We observe relatively parallel trends between the groups before the legalization month for some crime rates. However, there is an abnormal decreased around April 2020, which may be due to the COVID-19 lock-downs.



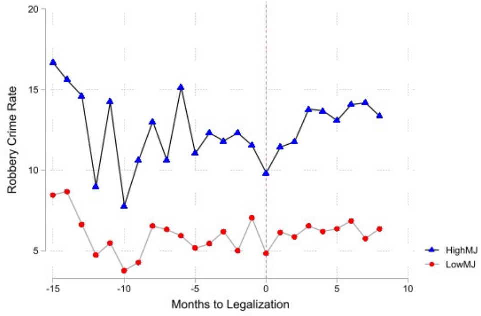

(a) Murder




(b) Rape

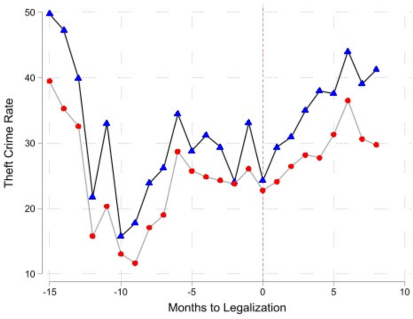



(c) Assault

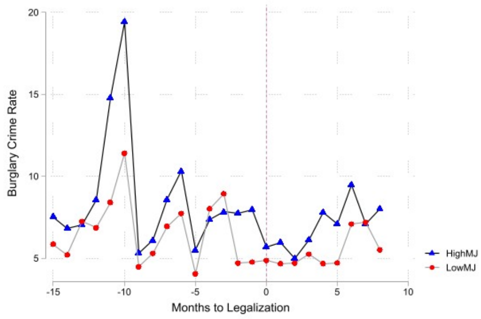



(d) Robbery

Figure 2: Trend visualization for all violent crime rates




(a) Theft




(b) Burglary

Figure 3: Trend visualization for all property crime rates

# 5 Econometric model

Our research design consists of a Two-way Fixed Effects (TWFE) Difference-in-Difference (DID) model. Such a design allows identifying the differentiated effect of the legalization of marijuana across police precincts in NYC according to their level of marijuana-related crime rates in a base year. To illustrate our procedure, we will first develop a classic DID approach in Model (1), then specify the TWFE DID in Model (2), and finally specify the TWFE DID that will allow us to test for the parallel trends' assumption.

Formally, let $C_{it}$ be the crime rate in precinct $i$ and year-month $t$, and define the following variables: $HighMJ_{i,2019}$ is a binary variable where $HighMJ_{i,2019}$ equals to 1 if precinct $i$ has a crime rate for marijuana-related arrests above the 2019 median, and $HighMJ_{_{i,2019}}$ equals to 0 otherwise. $Post_t$ is a binary variable such that $Post_t$ is equal to 1 if crime rate is observed after March 31, 2021 (post), and $Post_t$ is equal to 0 if the crime rate is observed before the legislation (pre-legalization). The DID is implemented parametrically in the following reduced-form linear model:

$$C_{it} = \alpha + \beta HighMJ_{i,2019} + \gamma Post_t + \delta HighMJ_{i,2019} \times Post_t + \varepsilon_{it} \tag{1}$$

where $\alpha$ is a constant, and $\varepsilon_{it}$ is the error term. Coefficient $\delta$ is the DID estimate of the change in crime rates in precincts with larger marijuana-related crime rates (as opposed to precincts with lower levels) between the pre and post periods. What is more, we can rewrite the model in 1 to account for precinct and time fixed effects, which allows us to net out unobserved local characteristics affecting crime that do not change over time, as well as those crime-related factors that vary over time but are common to all precincts.

$$C_{it} = \eta_i + \nu_t + \delta HighMJ_{i,2019} \times Post_t + \varepsilon_{it} \tag{2}$$

Then, the model in 2 is a Two-way Fixed Effects Difference in Difference (TWFE DID) specification, where $\eta_i$ is a precinct fixed-effect and $\nu_t$ is a (year-month) time fixed-effect.

## 6 Results

Following the methodology above, Table 2 shows the results for model described in equation 1, which is the standard DID approach. As we can see, the coefficients associated with the variable $HighMJ$ show the difference in mean between precincts in the high marijuana possession arrests group as opposed to the precincts in the low marijuana possession arrests group. Then, the coefficients associated with the variable $Post$ show the difference in mean between the period before and after the legalization of recreational marijuana in March 31st, 2021. Finally, coefficient $\delta$ associated with our variable of interest ($HighMJ \times Post$) shows the difference between high MJ precincts and low MJ precincts *after* the legalization of recreational marijuana (in the Post period). These are shown for all crime rates described in our Section 4.

Nevertheless, this specification does not exploit all the variance we could in order to correctly assess the effects of marijuana legalization on crime. Moreover, our main coefficient of interest might be biased by the omission of relevant variables. Table 3 presents the results for model in equation 2, the Two-Way Fixed Effects DID model, which introduces fixed effects at the precincts and year-month level. The precinct fixed effects are important because it allows us to control for different observed and unobserved local characteristics that affect crime rate but do not change over time. Likewise, time fixed effects control for different observed and unobserved characteristics changing over the months, but not across precincts, that also affect crime rates.

The results from our main specification show that the murder crime rate, a violent crime, has a positive and significant associated coefficient $\delta$. In this sense, we are able to reject the null hypothesis that $\delta = 0$, and provide suggestive evidence that, after the legalization marijuana for recreational purposes, there is a differential increase in the arrests for murder crimes for precincts with a higher presence of marijuana commercialization and police resources destined to chase it in 2019 (compared to precincts with a lower presence of it). We find no significant effect on other violent nor any property crime rates.

It is important to note that, considering earlier base years for high marijuana arrests (see Appendix A), the results are similar in expected directions of the effects. Furthermore, effects magnitudes are larger when estimations are run with earlier baselines (2016-2018). We find a consistent significant effect on murder crime rates. Additionally, effects on assault and theft crime rates seem to be positive and significant at the 5% level when using 2017 and 2016 base years.

Table 2: Results from DD specification

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All Crimes | All Violent | Murder | Rape | Assault | Robbery | All Property | Theft | Burglary |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| HighMJ: $\beta$ | 0.778*** | 0.690*** | 0.070*** | 0.010 | 0.510*** | 0.099*** | 0.088 | 0.080* | 0.008 |
| | (0.128) | (0.083) | (0.006) | (0.009) | (0.067) | (0.013) | (0.059) | (0.048) | (0.013) |
| Post: $\gamma$ | 17.972*** | 11.864*** | 0.565 | 1.305*** | 9.435*** | 0.559 | 6.108 | 8.764** | -2.656*** |
| | (5.902) | (3.080) | (0.492) | (0.477) | (2.489) | (0.704) | (3.923) | (3.984) | (1.008) |
| HighMJ×Post: $\delta$ | 0.020 | 0.034 | 0.021*** | -0.005 | 0.016 | 0.001 | -0.014 | -0.016 | 0.002 |
| | (0.050) | (0.037) | (0.006) | (0.003) | (0.033) | (0.007) | (0.025) | (0.025) | (0.007) |
| Constant | 101.346*** | 42.652*** | 2.106*** | 2.751*** | 28.655*** | 9.140*** | 58.693*** | 45.289*** | 13.404*** |
| | (13.681) | (5.992) | (0.437) | (1.030) | (4.438) | (1.443) | (9.310) | (7.263) | (2.250) |
| Observations | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 |
| $R^2$ | 0.191 | 0.484 | 0.433 | 0.010 | 0.487 | 0.190 | 0.006 | 0.009 | 0.005 |

*Note:* Significance level: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors at the precinct level in parenthesis.

Table 3: Results from TWFEDD specification

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All Crimes | All Violent | Murder | Sexual | Assault | Robbery | All Property | Theft | Burglary |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| HighMJ×Post: $\delta$ | 9.311 | 7.718 | 1.896** | -0.527 | 5.190 | 1.160 | 1.593 | 2.178 | -0.586 |
| | (9.466) | (4.922) | (0.727) | (0.567) | (3.542) | (1.480) | (5.598) | (5.362) | (1.373) |
| Observations | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 |
| $R^2$ | 0.875 | 0.880 | 0.634 | 0.761 | 0.868 | 0.621 | 0.810 | 0.774 | 0.488 |

*Note:* Significance level: *p<0.1; **p<0.05; ***p<0.01. Clustered standard errors at the precinct level in parenthesis.

# 7 Conclusions and next steps

From our results, we see that the legalization of recreational marijuana in NYC is associated with an increase in the number of arrests for murder crimes (and likely assault and theft crimes as well). Specifically, for murder we observe an increase of 1.89 arrests per hundred thousand inhabitants in precincts where the incidence of marijuana possession arrests was above the median for the year 2019. This represents an increase of 14.9% in murder arrests due to the legalization of marijuana. When we run robustness checks to see if a different base year to define which precincts have a larger presence of marijuana possession arrests, assault and theft crimes also face an increase in their crime rates by up to 8.16 (8.0%) and 12.16 (21.2%) arrests per hundred thousand inhabitants, respectively. This represents an increase of 14.9% in murder arrests due to the legalization of marijuana.

These results could be consistent with the literature presented by Dragone et al. (2019), where they argue that the decriminalization of marijuana possession is associated with a reallocation of police resources to other crimes, which could cause an uptick in non-marijuana-related arrests. Adda et al. (2014) also found an increase in crime rates followed by the decriminalization of marijuana possessions in one London borough. Similarly, they argued their findings were due to police resource reallocation to go after other crimes by showing results were not driven by a change in total police resources. However, for our project, we acknowledge that further exploration is necessary to claim this is the channel driving our findings.

For example, we could explore other databases such as the NYC Crime Claims, which includes all the claims made by citizens to the NYPD about possible crimes, including those that did not result in an arrest. Given the increase we have observed in arrests, if we were to observe that the number of claims does not change in our main specification, this could provide further support to our hypothesis that the legalization of marijuana resulted in the reallocation of police resources to pursue different types of crime. This follows because it is not that crime is rising but that police is able to make more arrests than before the legislation.

Likewise, we could take further steps to strengthen our research setting. For example, we tested for parallel trends in our setting for all crime rates, and we observed unusual behavior in all crime rates around April 2020, potentially due to COVID-19 lock-downs. This abnormal event could threaten our specification, since parallel trends are a key assumption in a difference-in-difference setting. Nonetheless, we should further explore the most recent literature in difference-in-difference to allow for the parallel trend assumption to be relaxed (Kahn-Lang and Lang, 2020).

Additionally, this study could benefit from geographic variation where we could compare the change in crime rate between New York City and other nearby cities in states that have not yet legalized recreational marijuana. This could potentially provide insight into country-wide trends in crime, and we could expand our control and treatment groups accordingly. According to the FBI and other data widely reported by many major new agencies, 2021 and late 2020 saw significant increases in crime rates nationwide (Witte, 2022). Thus, we should further test our to carefully isolate our results from these trends.

Since New York City is unique in its diversity and size in the United States, one potential method which could be used in order to ensure comparison with a valid counterfactual would be the creation of a synthetic control. As presented in Scott Cunningham's Causal Inference: The Mixtape, a synthetic control would be created by using a control group of other cities in which the units are assigned weights such that the outcome of these aggregated units looks and behaves very similarly to New York City. Thus, we could satisfy the parallel trend assumption and be reasonably content that the comparison was valid through the whole time period. Overall, the pursuit of such analyses would greatly benefit future conclusions about the impacts of the legalization of marijuana.

## References


Adda, J., McConnell, B., and Rasul, I. (2014). Crime and the depenalization of cannabis possession: Evidence from a policing experiment. *Journal of Political Economy*, 122(5):1130–1202. 3, 10

Anderson, D. M. and Rees, D. I. (2014). The legalization of recreational marijuana: how likely is the worst-case scenario? *Journal of Policy Analysis and Management*, pages 221–232. 3

Becker, G. (2014). Why marijuana should be decriminalized. *The Becker-Posner Blog*. 2

Becker, G. S. and Murphy, K. M. (2013). Have we lost the war on drugs? *Wall Street Journal*, 4. 2

Chimeli, A. B. and Soares, R. R. (2017). The use of violence in illegal markets: Evidence from mahogany trade in the brazilian amazon. *American Economic Journal: Applied Economics*, 9(4):30–57. 2

Crost, B. and Guerrero, S. (2012). The effect of alcohol availability on marijuana use: Evidence from the minimum legal drinking age. *Journal of health economics*, 31(1):112–121. 3

DiNardo, J. and Lemieux, T. (2001). Alcohol, marijuana, and american youth: the unintended consequences of government regulation. *Journal of health economics*, 20(6):991–1010. 3

Dragone, D., Prarolo, G., Vanin, P., and Zanella, G. (2019). Crime and the legalization of recreational marijuana. *Journal of economic behavior & organization*, 159:488–501. 2, 3, 10

Green, B., Kavanagh, D., and Young, R. (2003). Being stoned: a review of self-reported cannabis effects. *Drug and alcohol review*, 22(4):453–460. 2

Hall, W., Lynskey, M. T., and Degenhardt, L. (2001). *The health and psychological effects of cannabis use*. Commonwealth Department of Health and Ageing Canberra. 2

Kahn-Lang, A. and Lang, K. (2020). The promise and pitfalls of differences-in-differences: Reflections on 16 and pregnant and other applications. *Journal of Business & Economic Statistics*, 38(3):613–620. 10

Kelly, E. and Rasul, I. (2014). Policing cannabis and drug related hospital admissions: Evidence from administrative records. *Journal of Public Economics*, 112:89–114. 3

Witte, G. (2022). Homicide rates have soared nationwide, but mayors see a chance for a turnaround in 2022. *The Washington Post*. 10

# A Results from main specification defining High and Low marijuana precincts using 2016-2018 numbers

Table 4: Results from TWFEDD specification: HighMJ 2018

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All Crimes | All Violent | Murder | Sexual | Assault | Robbery | All Property | Theft | Burglary |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $HighMJ_{2018} \times$ Post: $\delta_{2018}$ | 15.855$^{*}$ | 10.907$^{**}$ | 2.904$^{***}$ | 0.582 | 6.443$^{*}$ | 0.978 | 4.948 | 6.216 | -1.268 |
| | (9.364) | (4.836) | (0.685) | (0.585) | (3.506) | (1.483) | (5.596) | (5.358) | (1.369) |
| Observations | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 |
| $R^2$ | 0.876 | 0.880 | 0.638 | 0.761 | 0.868 | 0.621 | 0.811 | 0.774 | 0.488 |
| *Note:* | Significance level: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Clustered standard errors at the precinct level in parenthesis. | | | | | | | | |

Table 5: Results from TWFEDD specification: HighMJ 2017

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All Crimes | All Violent | Murder | Sexual | Assault | Robbery | All Property | Theft | Burglary |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $HighMJ_{2017} \times$ Post: $\delta_{2017}$ | 22.537$^{**}$ | 11.980$^{**}$ | 2.036$^{***}$ | 0.539 | 7.143$^{**}$ | 2.263 | 10.557$^{*}$ | 12.158$^{**}$ | -1.601 |
| | (9.210) | (4.792) | (0.722) | (0.585) | (3.486) | (1.460) | (5.539) | (5.283) | (1.369) |
| Observations | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 |
| $R^2$ | 0.877 | 0.881 | 0.634 | 0.761 | 0.868 | 0.622 | 0.811 | 0.776 | 0.488 |
| *Note:* | Significance level: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Clustered standard errors at the precinct level in parenthesis. | | | | | | | | |

Table 6: Results from TWFEDD specification: HighMJ 2016

| | *Dependent variable:* | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | All Crimes | All Violent | Murder | Sexual | Assault | Robbery | All Property | Theft | Burglary |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $HighMJ_{2016} \times$ Post: $\delta_{2016}$ | 23.449$^{**}$ | 12.594$^{**}$ | 2.232$^{***}$ | 0.559 | 8.160$^{**}$ | 1.643 | 10.855$^{*}$ | 12.032$^{**}$ | -1.177 |
| | (9.180) | (4.774) | (0.714) | (0.585) | (3.459) | (1.470) | (5.530) | (5.286) | (1.375) |
| Observations | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 | 1,823 |
| $R^2$ | 0.877 | 0.881 | 0.635 | 0.761 | 0.869 | 0.622 | 0.812 | 0.776 | 0.488 |
| *Note:* | Significance level: $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01. Clustered standard errors at the precinct level in parenthesis. | | | | | | | | |