Drug Laws, Police Leniency, and Racial Disparities in Arrest Rates

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Abstract

This paper tests if racial disparities in arrests are driven by police bias. I use Chicago police arrest data with the quantity of contraband reported to determine if racial discrimination affects police decision-making at lower and higher contraband severity differentially. By showing there is a larger racial disparity in arrest rates at lower contraband levels than at higher levels, I provide evidence as to whether the disparity is driven by officer taste-based discrimination. I then run an interrupted time series in order to estimate the affect on the arrest rate disparity of decriminalization of marijuana in Illinois at different severities. My results motivate policy decisions to decriminalize marijuana and, subsequently, other minor crimes that disproportionately harm minority groups.

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1 Introduction

Decades of research[1] has provided a profound volume of literature showing evidence of racial disparities in the criminal justice system in the U.S., including in traffic stops, arrests, sentencing, bail setting, and parole decisions. These differences can stem from a multitude of underlying factors, such as social differences, income level, gender, etc. Inequitable treatment by law enforcement, the justice system as a whole, can lead to further issues, such as the poverty cycle and social unrest. Therefore, policymakers across the U.S. have long tried to adjust laws to ensure equitable and just practices are incorporated. Unfortunately, research shows this has been largely ineffective. Thus, it as an issue that still must be dealt with. Researchers must first determine the origins of these disparities in order for effective solutions to be developed and implemented. Discrimination in the U.S. justice system weakens its effectiveness and fails to remain impartial and apply equal rights and punishments to citizens.

If citizens believe police officers, judges, or other law enforcement will not be impartial, then they may be less likely to report a crime. Lack of trust in the police might lead to ineffective law enforcement; for example, if a minority individual fears there is a break in at their neighbor's house. Uncertain that police will not arrest them or think they were in some way involved might lead the individual to delay or refrain from calling the police altogether. There is not much research available describing how trust in law enforcement affects reporting, but it is logical to assume fear of being wrongly arrested, and therefore lack of trust in the justice system, might deter someone from calling the police when they witness a crime. Additionally, racially prejudiced decisions could mean government resources are wasted on detaining, holding, and rehabilitating individuals who may not necessarily deserve as much time in jail. Alternatively, those who might otherwise deserve to be in jail might go free due to an officer using their own discretion in a particular arrest and allowing a individual to go free when they may actually have broken the law only because they are white. There is the direct ineffectiveness here due to the individual not facing any legal consequences, but it also sends a signal that even getting caught might not lead to them being arrested; they may then be more likely to commit crimes in the future. The inability to remain impartial then results in many circumstances where the justice system breaks down.

It is the goal of the criminal justice system to impose laws and policies that equally benefit and punish

[1] Anwar and Fang (2006), Donohue and Levitt (2001), Abrams et al. (2012), Mustard (2001); Arnold (2018); Arvanites and Asher (2006); Rehavi and Starr (2014); West (2018)

people of any and all races, rather than disproportionately punishing or favoring individuals of a certain race. In fact, Justice Lewis Powell Jr. said "Equal justice under law is not merely a caption on the facade of the Supreme Court building, it is perhaps the most inspiring ideal of our society. It is one of the ends for which our entire legal system exists... it is fundamental that justice should be the same, in substance and availability, without regard to economic status."[2] Government resources are wasted when their tools are applied inappropriately and ineffectively.[3] Racial prejudice could lead government resources to be wasted on detaining, holding, and rehabilitating individuals who may not need it; or others go free due to an officer using their own discretion in a particular arrest when they may actually have broken the law only because they are white. There is the direct ineffectiveness due to the individual not facing any legal consequences, but also sends a signal that even getting caught might not leading to fewer crime disincentives. A lack of impartiality then leads to the justice system failing on a fundamental level. Therefore, it is necessary to accurately determine if the evolution of laws is pushing toward or away from equity. This paper specifically focuses on the equity of law enforcement and aims to determine the mechanisms through which arrests occur at disproportionately higher rates for minorities. Information excluded from police reports can skew the data leading to inaccurate estimated outcomes for stops and arrests because it fundamentally involves latent outcomes. Specifically, if officers choose not to report something systematically for individuals of a particular race, we would not know if these drivers did, in fact, break certain laws–I will give a more specific example related to this issue in the next section. Therefore, I look at arrest outcomes from a different angle. Taking that contraband is found at a stop as given, I determine that there are differing racial disparities in the rates at which arrests occur at different levels of severity.

Mustard (2001) shows that sentencing, especially for drug-trafficking offenses, disproportionately harms blacks and Hispanics. The sentencing disparity is even primarily driven by departures from the sentencing guidelines. The implication, here, is that judges make the decision to give harsher sentences to minorities, regardless of not making these decisions for white or wealthier individuals. It is unclear if these are conscious or subconscious harsher sentences. Regardless, it is clear that white people may be more likely to have less harsh sentences. If this same sort of disparity enters into the previous phase of law enforcement, then it may present in such a way that police officers are more likely to arrest minorities

[2] Supreme Court Associate Justice 1971 to 1987.

[3] There is not much research available describing how trust in law enforcement affects reporting, but it is logical to assume fear of being wrongly arrested, and therefore lack of trust in the justice system, might deter someone from calling the police when they witness a crime.

to whites for the same offenses. Additionally, it is reasonable to assume that these disparities are more likely to occur for lower level offenses. In order to address this, I use data on stops and arrests which include measures and types of contraband that allow me to see the severity of the contraband found. I then compare the disparity in arrest rates for minorities at multiple levels of severity to determine whether disparities are higher for lower levels of contraband, such as possession of a small amount of marijuana. If arrests occur at disproportionately higher at lower contraband levels, then this indicates that harsher drug laws that criminalize marijuana are more likely to lead to racial disparities in arrests. In this case, it is more equitable to relax marijuana laws in order to decrease the costs of racial prejudices within the justice system. In this paper, I look at racial disparity in arrest rates over several severity levels of contraband found on an arrestee to determine one way marijuana law relaxation can lead to positive social effects in the criminal justice system.

This paper contributes to a broad spectrum of literature examining the prevalence of racial discrimination in the criminal justice system and to more recent literature examining the consequences of marijuana legalization laws. Knowles, Persico, and Todd (2001) develop the KPT model to estimate discrimination that is expanded upon later by other researchers.[4] Bjerk (2004) develops a model to include a noisy signal of guilt and tests it to find it is difficult to determine if there is racial discrimination or if statistical discrimination can explain the arrest disparity. Antonovics and Knight (2009) find that police officers in Boston are less likely to conduct a search if the race of the officer matches the race of the driver and vice-versa. Alesina and La Ferrara (2014) find that death sentences of minority defendants convicted of killing white victims are more likely to be reversed on appeal. Additionally, Abrams et al. (2012) show that there is between-judge variation in incarceration rates. Ryan (2015) shows that interaction of the gender of the driver, the time of day of the traffic stop, and the existence of passengers in the stopped vehicle with the race of the driver all impact the probability of receiving a frisk. Alternatively, Anwar and Fang (2015) fail to reject the hypothesis that troopers of different races do not exhibit relative racial prejudice, though their model is prone to type-II errors, so this result is somewhat inconclusive. There is also a large literature examining racial discrimination in other settings, such as the labor market[5], the provision of healthcare[6], and the sharing, housing, sports, and credit markets.[7]

[4] Anwar and Fang (2006). Donohue and Levitt (2001) looked at the effect on arrest rates based no the demographics of officers.

[5] Lang et al. (2005) and Goldin and Rouse (2000)

[6] Anwar and Fang (2012)

[7] Edelman et al. (2017), Schafer (1979) and Edelman et. al (2017), Hamilton (1997), Dougal et al. (2019), Storey

There are several reasons we might care about the potential positive effects of marijuana legalization. First, it can help determine positive social effects through increased police trust and equitable treatment of different races. It can also help determine a means of reducing behavioral differences in justice system, so laws can specifically target reducing racial disparities in arrest rates. Additionally, a drop in arrests for misdemeanor drugs might allow officers to focus on more serious drug activity and allowing resources to be spent more wisely on more harmful and costly crimes. Finally, it helps provide evidence for marijuana legalization, and subsequently for other minor legal offenses that might disproportionately favor individuals who are white or wealthy.

There is a large volume of literature suggesting that a portion of the racial disparities in the criminal justice system come from discrimination.[8] However, there is often little evidence this is caused by taste-based (rather than statistical) racial discrimination. This research aims to show the magnitude of the racial disparity due to taste-based discrimination in arrests for contraband using leniency. I will test for the unobservable leniency exercised by police officers toward white individuals in this paper.

Consider the following example: a police officer stops a white male college student and notices he has a couple grams of pot in his center console. Since he is a young white man, the officer decides to pretend he did not notice. The stop is reported, but the marijuana possession is never written down. Therefore, this stop does not end up in the data. If a young black man is stopped in the same situation and racial bias factors into the officer's decision on how to proceed, he likely will take further action and arrest the man for possession of marijuana. If both drivers had heroin on them, the officer would likely not show leniency in either case as it is a schedule one drug.

Hit rate models will be biased toward no disparity if officers are systematically reporting a hit equal to 0 where it should be 1 for individuals with certain characteristics. It will appear the disparity is caused by statistical discrimination, i.e. black people are more likely to have drugs, but really is due to taste-based discrimination, i.e. the officer chose not to report the white driver's contraband. Therefore, another method is needed to try to tease out the effect of an officer's leniency that does not appear in the data, rather than simply looking at hit rates. By looking at different contraband severity–where low severity would be a small

(2004), Bocian et al. (2008), and Dhakal (2019)

[8] Abrams et al. (2012), Mustard (2001): sentencing; Arnold (2018): stops; Arvanites and Asher (2006): imprisonment; Rehavi and Starr (2014): mandatory minimums; West (2018): traffic citations

amount of a non-dangerous drug, e.g. 1g of marijuana, and high severity would be larger quantities, e.g. 5oz of marijuana–I can compare the arrest racial disparity at lower levels of contraband to that at higher levels, giving a better idea of how much racial prejudice affects the arrest rate. If the disparity is smaller at higher levels, controlling for individual and stop characteristics, this indicates police discretion explains the disparity at lower levels. This implies taste leads to less leniency for minorities at lower offense levels. I discuss this further in the Methodology section.

The data used in this paper are individual arrests from Chicago spanning 2016-2019 and totaling approximately 400,000 observations. The data includes the time and location of each stop, contraband found and its corresponding severity, race, gender, vehicle description, and other individual characteristics, e.g. age, sex, hair and eye color, etc. Using this detailed data, I can see whether a driver is arrested for a gram of marijuana or a gram of heroin, and whether the driver is white. If there is a larger racial disparity of arrests for lower levels of drug contraband, then this implies police discretion might be a determining factor in the arrests for smaller drug crimes, allowing racial prejudices to seep into the decision-making process. Thus, I employ a linear regression model to first find the difference in arrests rates, then find the difference in this disparity at each contraband level and determine if there is evidence of unequal treatment at lower levels.

In the next section, I provide a thorough explanation of Laws on marijuana possession within Illinois followed by a discuss the analysis of arrest rate disparities conducted in the literature thus far. In Section 3, I discuss the data used for this research, and in Section 4, I detail the analytical approach used here. In Section 5, I discuss the empirical results the data yield. I then conduct a sensitivity analysis and discuss shortfalls in the estimation approach used herein. Section 7 concludes the paper and discusses the implications and future avenues for research to add to and improve upon the information presented.

2 Background

2.1 Illinois Marijuana Laws

Throughout the period of the sample data, there have been multiple changes to Illinois state laws regarding possession and consumption of marijuana. Prior to July 29, 2016, The Cannabis Control Act–that was originally passed in 1978–outlined the laws surrounding marijuana use. Up to this point, possession or use of less than 2.5 grams of marijuana was a Class C misdemeanor with a fine of $100-$200. Possessing 10g-30g was a Class A misdemeanor. Possession of 30 grams or more was a felony, where classes increase with amounts. In order to improve law enforcement effectiveness for more violent and severe crimes, the penalties and classification of the aforementioned crimes were reduced. The most notable change was the decriminalization of possession of smaller amounts of cannabis.

On July 29, 2016, Public Act 99-0697 was enacted, thereby amending the Cannabis Control Act. This act states that possession of up to 10 grams of cannabis is a civil law violation punishable by a fine between $100-$200 and removes the class C misdemeanor status of possessing less than 2.5 grams of cannabis, as well as the class B misdemeanor status of possessing 2.5g-10g of cannabis. This act makes possession of 10g-30g of cannabis a class B misdemeanor and possession of 30g-100g of cannabis a class A misdemeanor (down from a felony). Possession of 100 grams or more remains a felony that increases in class as the amount in possession increases. A class C misdemeanor could result in up to 30 days in jail, while a class B misdemeanor could result in up to 6 months. A felony charge for marijuana possession carries a mandatory minimum of one year in jail and could result in up to 6 years. Thus, these changes to the Cannabis Control Act mean that individuals found in possession of up to 10 grams of marijuana will not face the possibility of jail time, but be sentenced to jail time if they have more than 10 grams, dependent upon the judge assigned to the case and various other legal factors.

Moving forward, the Illinois legislature began discussing the possibility of legalizing recreational sale and use of marijuana over the following two years before introducing to the state senate Public Act 101-0027. After the state legislature passed this bill, governor Pritzker signed the bill on June 25, 2019, to officially take effect on January 1, 2020. Thus, the Cannabis Control Act of 1978 became partially obsolete. In this act, under Article 10, personal use of cannabis by individuals 21 year of age or older is legal. This is, of course, provided that they do not carry more than the legal limit of 30 grams of cannabis. Carrying over the legal limit results in the same charges outlined in Public Act 99-0697. Additionally, anyone under 21 years of age found in possession of marijuana faces a fine for a civil law violation.

In addition to changes in marijuana laws, there was another major change that affected the arrest rates in Chicago. In order to reduce the amount of discretion officers could use in stops related to stop and frisk. After this change in stop and frisk policies, officers are required to report reasoning for each stop and all officers are now required to receive training directed at ensuring each stop is made due to "reasonable suspicion of criminal conduct." l. On May 30, 2015, senate bill 1304 passed the Illinois Congress and it was signed into law officially on August 12, 2015. This was as part of Public Act 099-0352.

As part of their requirements to report reasoning for each stop, the data for these stops must now be collected and later released to the public. This is must explain all of "the reasons that led to a protective pat down and whether it was with consent." This potentially decreases arrests due to stop and frisk, which directly impacts marijuana arrests as a portion of these are a result stop and frisks.

2.2 Literature Review

Abrams et al. (2012) measure the between-judge variation in the difference in incarceration rates and sentence lengths between black and white defendants in felony cases from Cook County, Illinois. using a Monte Carlo simulation in order to construct the a counterfactual, in which race has no influence in sentencing. They find significant between-judge variation in incarceration rates, although not in sentence lengths. These results mirror Arvanites and Asher (2006) who show that there is a positive and significant effect of race on imprisonment rates, though the indirect effect is greater than the direct effect. However, Abrams et al. (2012) contrasts with Mustard (2001), who does find evidence that judges make the decision to give harsher sentences to minorities, regardless of not making these decisions for white or wealthier individuals. Additionally, Rehavi and Starr (2014) find that black individuals are 1.75 times more likely to face a charge carrying a mandatory minimum than white individuals. Though these are not necessarily harsher sentencing decisions by the judge, these charges automatically come with a minimum prison sentence and could exacerbate sentencing differentials. The data in this paper span a multitude of legal regimes under which larger amounts of marijuana possession carry a mandatory minimum until legal restrictions on marijuana are relaxed. The cutoff for mandatory minimums sends a signal of severity and can affect the distribution of arrests. Here, we would expect that racial prejudices do not play a role in the decision to arrest when marijuana is found.

There is less research into the disparity in bail setting. However, using estimates from Miami and Philadelphia, Arnold et al. (2018), tests for racial bias in bail decisions. They show that bail judges are racially biased against black defendants, with more racial bias among inexperienced and part-time judges. In addition, they find that both black and white judges are biased against black defendants; therefore, they argue that this is consistent with bail judges making racially biased prediction errors, rather than being racially prejudiced, meaning they find evidence of a statistical bias.

In order to deal with the difficulty of teasing out taste-based racial bias in traffic citations, West (2018) examines automobile crash investigations for which officer dispatch is exogenous to driver race. He finds that state police issue more traffic citations to individuals of a different race from their own, indicating a preference for discriminatory leniency towards same-race individuals. Additionally, Donohue and Levitt (2020) use panel data from 122 large U.S. cities to show that increases in the number of minority police are associated with increases in arrests of white individuals, but have little impact on arrests of minorities. Similarly, more white police officers is associated with an increase in the number of arrests of minorities but do not systematically affect the number of white arrests. They estimate that maximizing same-race policing would lead arrests to decrease by over 15 percent.

Grogger and Ridgeway (2006) examine the disparity in police stops and do not find evidence of racial bias, though Pierson et al. (2019) re-examines this model using a larger, broader dataset across dozens of U.S. cities and find that there is a disparity in stop rates. Feigenberg and Miller (2020) use unique Texas administrative data to isolate variation in search behavior across sate troopers. They find that search rates are unrelated to the proportion of searches that yield contraband. According to their results, troopers appear unable to distinguish between those who are more or less likely to carry contraband. Knowles et al. (2001) do not find evidence of racial prejudice against black drivers. They note that, if police have utility only for searches yielding large drug finds, then their analysis would suggest bias against white drivers. However, they provide no argument as to why they believe police have a higher utility for larger drug finds. In their model, they show that, if troopers are not racially prejudiced, all motorists must carry contraband with equal probability regardless of their race and other characteristics, in equilibrium. However, this implies that a motorist's characteristics other than race do not provide information about the presence of contraband when a trooper decides whether to search. However, trooper guidelines require officers to base their search decisions on the information the motorist presents to the trooper at the time of the stop, such as their demeanor and the contents of their vehicle that are in plain view. (Riksheim and Chermak 1993). Anwar and Fang (2005) allows the possibility that police behavior might vary by racial group by relaxing the assumptions made by KPT by using race-matchin, using Florida data that provides race of the trooper in addition to driver's race. When replicating the KPT test, the result immediately implies that the troopers show racial prejudice against black and Hispanic motorists. However, this conclusion is only valid if their model of motorist and trooper behavior is true. Anwar and Fang's (2005) results show that, without strong assumptions, they cannot confidently prove the presence of relative, racial prejudice within the modified KPT framework. Cox and Cunningham (2017) estimate the effect of a federal grant program as part of the 1988 Anti-Drug Abuse Act to combat illicit drugs and provide evidence that federal involvement in narcotic control and trafficking leads to an increase in drug arrests; disproportionally affecting black individuals. This implies that targeting drug use leads to a larger racial disparities and relaxation of these policies may lead to a smaller racial disparity in arrests, and therefore a smaller disparity in drug-related crimes that lead to prison sentences. This could reduce the disparity at numerous levels of the criminal justice system and could instead allow funding, such as the ADAA grant, to fund reduction of other more violent crimes or to fund drug abuse mitigation through recovery for addicts.

There is some evidence of racial bias at each stage of the criminal justice system, though the magnitudes of this are still disputed, as is the underlying cause for the disparity, i.e. whether the estimates accurately estimate taste-based racial bias or statistical bias. The aim of this paper is to asses how much of the racial disparity in arrests is due to racial bias and what portion of this is due to statistical vs taste-based preferential treatment by race.

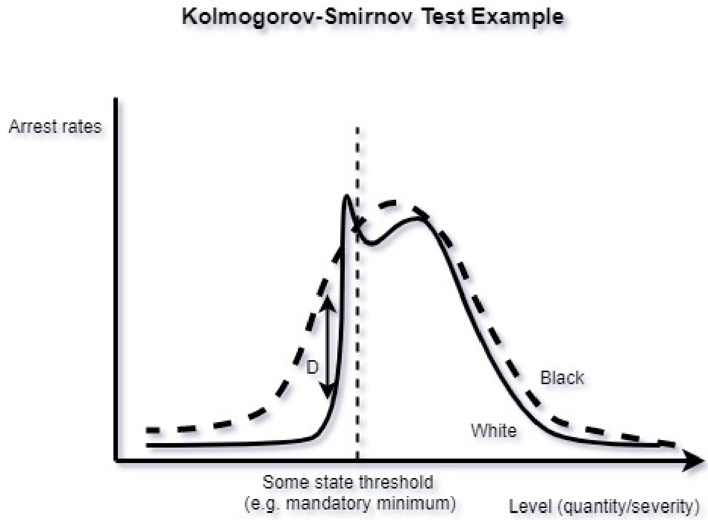
2.3 Kolmogorov-Smirnov Test

The Kolmogorov-Smirnov (KS) test is a non-parametric and distribution assumption-free test. It requires no assumptions to be made about the distribution of the data. The KS test can be used to compare a sample with a reference probability distribution, or to compare two samples. These two aspects of the test make it versatile. In order to determine if the two data samples I am interested in, arrest rates of black vs white people, the KS test can be used. The null hypothesis is that the samples do indeed come from the same distribution; if we reject the null, then we accept the alternative hypothesis that the samples do not come from the same distribution.[9] To clarify this test, I provide a hypothetical illustration in Figure 1.

The estimated D is the maximum difference between the two distributions. This tells the biggest difference, but the p-value from this test gives more information. With a small enough p-value to find significance, we can say that the distributions are statistically significantly different. However, this simple

[9] Motivation for when to use the KS test is detailed by Kawwa (2020) and Lopes et al. (2007)

Figure 1



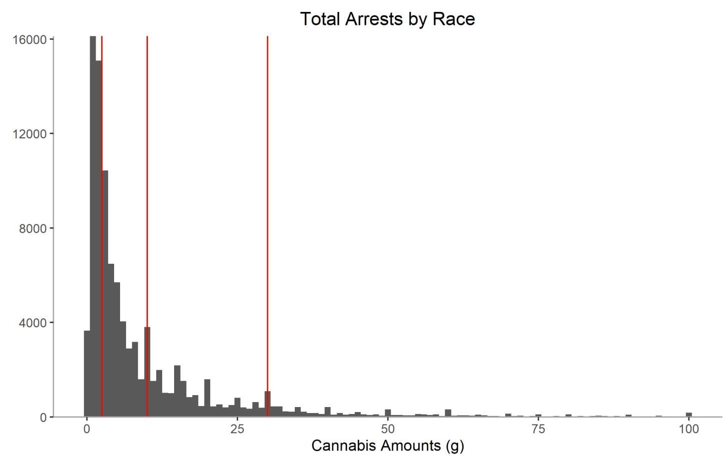
test does not provide information on what ways the distributions differ. For this, further analysis is needed through plots and regression analysis. For this paper, I use the KS test to determine whether the distribution of white arrest rates and black arrest rates over quantity differ over the whole distribution, then whether they differ specifically in the lower and higher quantity regions. I will expand upon this further in the methodology section 4.

3 Data

The data used in this paper are contraband arrests from Chicago, IL from January 1, 2012 to October 19, 2020. This data was procured through a FOIA request that has been ongoing for much of 2020 and was released to me in October 2020 by the Data Fulfillment and Analysis Section in the Strategic Data Analytics Division of the Chicago Police Department. There are nearly 220,000 contraband arrests, almost half of which are specifically marijuana arrests, which is the primary subset I focus on in the following analysis. The data includes the time and location of each stop, amount of contraband found, individual's name, race, gender, and other individual characteristics, e.g. age, sex, hair and eye color. I also received these same characteristic descriptions for the arresting officer. Approximately 79% of the individuals arrested for marijuana possession are black with less 5% being white and 7% Hispanic. Of the overall dataset, approximately 78% are black and 6% are white, with approximately 15% Hispanic.

The incidence of arrests at each weight are shown in Figure 2. The vast majority of all marijuana arrests occur at less than 100 grams. Any possession of marijuana 30g or more is a felony under Illinois laws with 30g-100g being downgraded to a Class A misdemeanor when legalization occurs. The laws for possession of marijuana up to 30g change over the sample period, with 2.5g or less being the least severe bracket. Between 10g-30g is still relatively low severity due to it's decriminalization status as of 2016 and makes up about one-third of the marijuana arrests. Any possession under 30g is considered legal as of 2020.

Figure 2

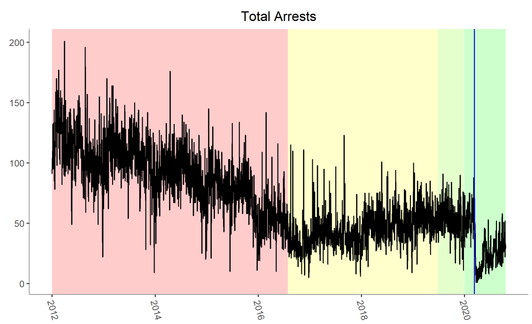


The time series plots in Figure 3 show the arrest rates across the data period for each race. Panel 3a shows the arrests for entire dataset, including arrests for non-cannabis related controlled substance possession arrests. Panel 3b shows the arrest rates for just individuals carrying marijuana. The shaded regions indicate changes in the policies for legal marijuana possession and use in Illinois. There is an overall downward trend for all contraband arrests with a few noticeable jumps, or trend changes that seem to correspond with policy shifts, and of course a Covid-19 shock at the very end of the data period. Looking at 3b, it is notable that there appears to be a drop when decriminalization occurs at the start of the yellow region, but the more dramatic shift here is the change in the overall trend. It seems to flatten out, which is possibly due to a more stable enforcement policy, though it there are other possible explanations. Looking at the start of the green section, it is difficult to see a drop in arrest rates due to legalization, which may be because decriminalization already occurred for overlapping amount brackets that legalization applies to.

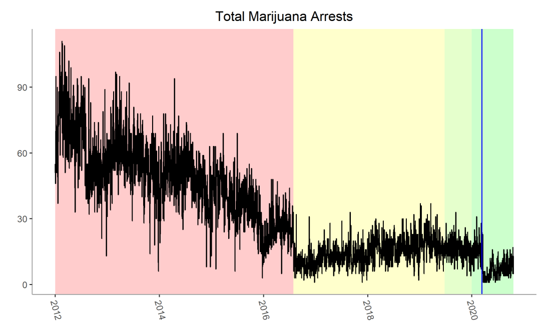
Less than 10 grams was already a civil law violation requiring no arrests and 10-30 grams was a class B misdemeanor. Therefore, up to 10 grams already did not lead to any arrests during the yellow region, prior to legalization.

Figure 3

(a)



(b) Marijuana Arrests

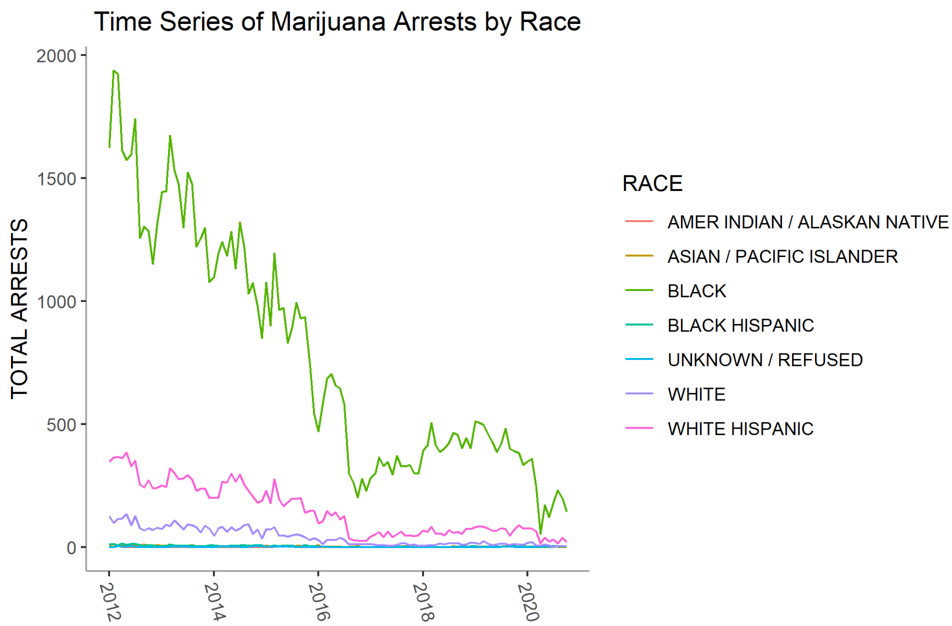


These trends are broken up by race in Figure 4. It clear here just how large the difference in number of arrests is over the sample period. Additionally, although all races do follow a similar trend, we can see that the overall trends are largely driven by the changes in arrests of black people.

The makeup of the marijuana arrest data are explained by Figure 5a and Figure 5b, for all races then for white and black individuals only, respectively. Here, you can see that the incidence of marijuana arrests is higher for black individuals for smaller amounts (in grams) of marijuana in their possession, but this may not be true for larger amounts. The vertical red lines show the cutoff amounts based on IL state laws for marijuana. Looking at the histogram, it is possible that bunching behavior is occurring at the lower bounds of each legal bracket, especially for black individuals.

Moving into the analysis, the density of arrests will be important, as I need to test my hypothesis in order to motivate the next step of my analysis. Figure 6 shows the density plot of marijuana arrests for white and black individuals. Before testing the density, it seems plausible that my hypothesis is supported by

Figure 4



the data since, at the lower severity end, there is a noticeable racial disparity; however, at higher severities, the disparity actually flips–though I postulate that this disparity will not be statistically significant. This preliminary figure supports the idea that other papers estimating the racial disparity across all severities are picking up the average across the whole distribution and, therefore, their estimates are likely biased toward zero. Further support will be provided in the next section where the KS test is performed.

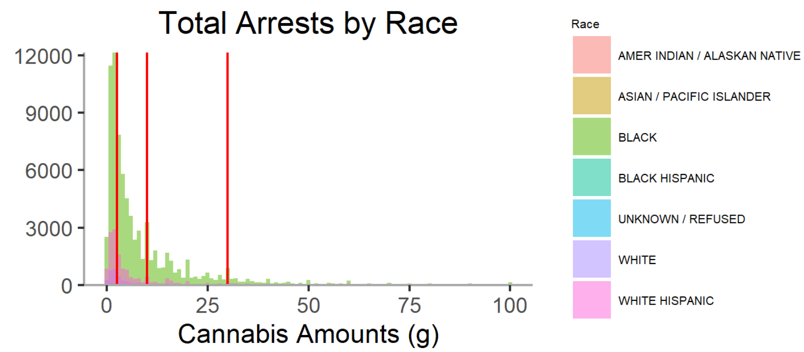
4 Methodology

4.1 Kolmogorov-Smirnov Test

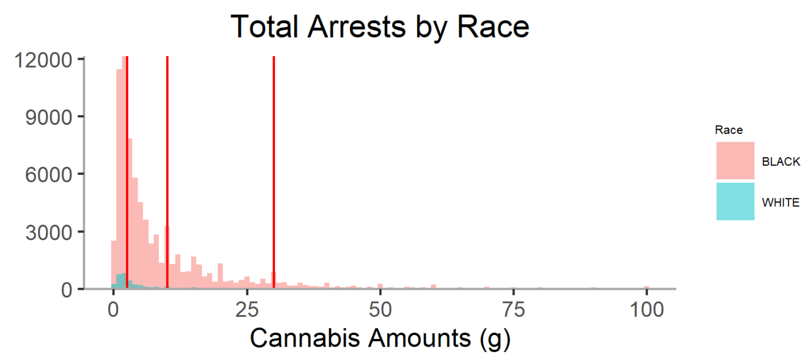
To test whether the difference in arrest rate density is significantly different between white and black individuals, I first use the Kolmogorov-Smirnov (KS) test. This tests if the CDFs of each set of data are the same. I hypothesize that the distribution for arrests at lower contraband levels shows higher densities for blacks, but higher levels are statistically similar. In order to test the lower and higher parts of the CDF separately, I must run the KS test twice. The cutoffs I use are the levels at which marijuana possession

Figure 5

(a)



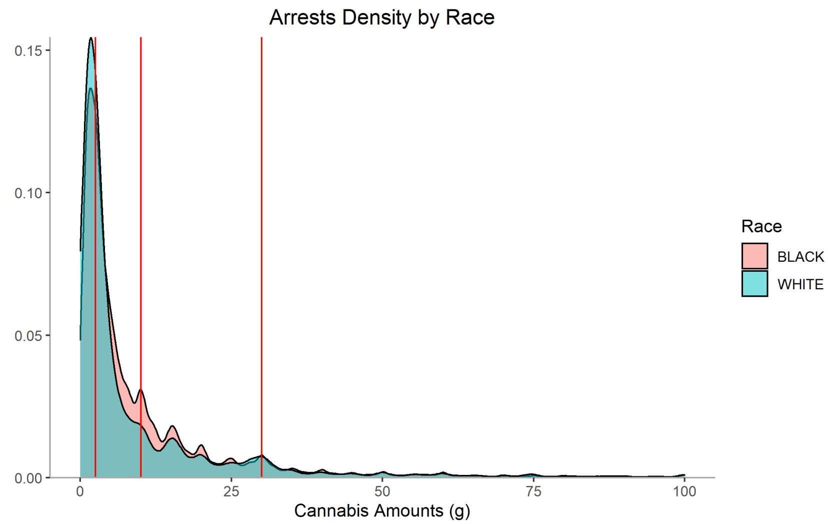
(b)



sentencing carries a higher citation and penalties or a mandatory minimum, which is legally mandated by the state of Illinois. Where previous research often finds small or no racial bias using a simple hit rate model, this distribution comparison might find more evidence of racial bias because it shows if there are differences in behavior of officers at different levels of severity. If this is occurring, then previous papers understate racial bias by concluding arrest rates are higher for blacks, so the disparity is explained by the higher propensity to commit a crime based on race. However, their results are missing some criminal behavior on the part of white individuals. The distance, D, on the left tail is the region where white people are actually committing crimes that would lead to arrest, but that are not reported.

The Two-Sample KS test shows that the two samples follow differing distributions for smaller, but not larger, amounts. The I compare are the those from below 10 grams, then below 30 grams, then 30 - 100 grams, 100-300 and 300 - 500, since, for IL, these are the legal cutoffs. Therefore, this is where policy

Figure 6



changes are likely to lead to more heterogeneity in arrest rates. Additionally, I choose to then exclude outliers in the higher weight range. It is prudent to do this because there are a small number of extremely large amounts, e.g. over 200,000 grams, and are likely to be associated with drug cartel or large gang busts, rather than average individuals. Large busts like this occur very infrequently and it is reasonable to assume individuals of these gangs are more likely to share race due to the segregated nature of gangs as described by Hagedorn (2006). Thus, there is more likely to be a one time jump in the distribution by race and can throw off the estimates for larger amounts that otherwise follow a similar distribution. As is shown in the previous plots, I choose to use 100 grams as the higher cutoff because it is a natural legal threshold, above which possession is classified as a class 4 felony.

One shortcoming of this portion of the analysis is that there is potentially a systematic difference im how black vs white people choose the amounts of marijuana which they carry. However, according to Keyes et al. (2017), many epidemiological studies of race/ethnicity and marijuana use have found that among adolescents, white adolescents are more or equally likely to use marijuana than their black peers. While some studies of adults indicate that Black Americans surveyed in 2012–2013 had higher rates of cannabis use disorders than whites, other surveys of the same sampling found that white adults had higher rates. Additionally, according to Feigenberg and Miller (2020), during routine traffic stops, police are more likely to search black and Hispanic motorists for contraband than white motorists, yet searches of black and

Hispanic motorists are equally likely to yield contraband. Chung et al. (2006) notes that their results show that rates of use of marijuana among black youths tend to be lower than among their white counterparts and note that this is confirms a "well-known" result. In my data, the average age of back individuals is 26 with white being 27. The 90th percentile for black arrestees is only 39 (41 for white), so the data consists of more young adults than older. This suggests that there is no reason to expect use of marijuana to differ by race and quantity to the extent that this test shows occurs in arrest rates in this systematic way.

4.2 Linear Model

Differences in the distribution also mean that the outcomes of standard hit rate models, implying either statistical or taste-based discrimination, are not trustworthy. It misses crucial information about the change in the mean over different levels of severity. I re-examine the link between subjective perceptions and objective measures of race discrimination by estimating the mean over several severity brackets in the distribution of arrest rates between white and black arrestees in order to decompose the race arrest rate disparity into the part attributed to different driver characteristics and the part attributable to differential treatment at points other than the conditional mean. To do so, I employ a linear regression, then take the difference between two severity ranges of the arrest rate densities between white and black individuals.[10] This gives a more precise estimate of the disparity at different severities that is conditioned on driver and stop characteristics. I start with my hypothesis.

Hypothesis: Officers are more likely to show leniency for less severe offenses than for more severe ones.

Hit rate models tend to be some variation of this baseline model

$$hit_i = \beta_0 + \beta_1 Black_i$$

The problem is, this model's estimates depend on police reporting of "hits."

$$hit = \begin{cases} 0, & \text{when no contraband is found} \\ 1, & \text{when contraband is found} \end{cases}$$

[10] Tuttle (2019)

If an officer shows leniency to an individual and chooses to not arrest them for illegal contraband, they must report a 0; otherwise, they are obligated to take legal action as is dictated by their precinct, local laws, and federal laws. This means there appear to be more 0s than what occurs in reality because a 1 was not reported when a hit occurred.

The KS test is consistent with the idea that standard hit rate model outcomes are biased because of latent variables they do not account for. Therefore, I employ a linear regression approach then decompose the arrest rate racial disparity into the part attributed to different statistical discrimination and the part attributed to differential treatment. The baseline model for race group r in quantity group q in month t is

$$arrestrate_{rqt} = \beta_0 + \gamma_1(\text{Race} \times \text{Quantity})_{rq} + \epsilon_{rqt} \tag{1}$$

This allows me to estimate equation 1, while using this approach. I find the disparity in the lower and higher severities, then take the difference in those disparities:

$$\gamma_1^{B1} - \gamma_1^{W1} = \beta_1^1 \tag{a}$$

$$\gamma_1^{B4} - \gamma_1^{W4} = \beta_1^4 \tag{b}$$

$$\beta_1^1 - \underbrace{\beta_1^4}_{\text{Statistical}} = \underbrace{\widetilde{\beta}_1}_{\text{Taste-based}} \tag{c}$$

where q=1 is the lowest severity. I then run the equation (1) again and add a time fixed effect to the model.

$$arrestrate_{rqt} = \beta_0 + \gamma_1(\text{Race} \times \text{Quantity})_{rq} + \gamma_2\alpha_t + \epsilon_{rqt} \tag{2}$$

This ultimately provides a more precise estimate of taste-based racial discrimination by differencing out the statistical discrimination in the racial disparity.

4.3 Interrupted Time Series

Given that changes in arrest laws may change the size of the disparity in arrest rates, I estimate the effects law changes in Illinois using an Interrupted Time Series.[11] This helps to determine if relaxation of

[11] I follow the methodology for ITS outlined by Bernal et al. (2017)

marijuana laws affects the disparity in arrest rates, as well. [12] Knowing that quantity does have an effect on the disparity, I then estimate the interrupted time series taking quantity into account. This is important because policies targeting the arrest rate disparity in marijuana may need to be adjusted to depend on where this disparity is coming from, i.e. the quantities of possession that drive it.

In order to test the effect on the arrest rate disparity of relaxing marijuana laws, I conduct an interrupted time series (ITS) around decriminalization. I begin with the following model that assumes both the level and slope of the arrest rate are affected by decriminalization.

$$arrestrates_{rt} = \delta_0 + \delta_1 \text{Day} + \delta_2 \text{Decrim} + \delta_3(\text{Day} \times \text{Decrim}_t) + \upsilon_{rt} \tag{ITS 1}$$

where r=race and t=day. It is possible that this policy shift leads to a response model wherein marijuana decriminalization leads to a change in the level of the arrest rate, but not a change in the slope over time. Therefore, I then run the following variation on ITS 1:

$$arrestrates_{rt} = \delta_0 + \delta_1 \text{Day} + \delta_2 \text{Decrim} + \upsilon_{rt} \tag{ITS 2}$$

Additionally, it is feasible for decriminalization to lead to a change in the slope of the arrest rate, but not a change in the level. To estimate this case, I run the following:

$$arrestrates_{rt} = \delta_0 + \delta_1 \text{Day} + \delta_3(\text{Day} \times \text{Decrim}_t) + \upsilon_{rt} \tag{ITS 3}$$

After running these three models for the overall dataset, as well the low vs high quantity groups, I determine the most likely appropriate response model based on the estimates. Based on the visible trend in time series of arrests in Figure 4, I posit that ITS 1 will be the most appropriate model to describe the policy change effect. In the final time series estimation, I use the best model estimated for each quantity group and run the model for each race, independently, to determine how the arrest rate changes for each race due to decriminalization. The results from these regressions are reported in Tables 3 through 6. I will discuss these estimates in the results section 5.3.

[12] Recall that the regions are color coded in Figure 3b

5 Results

5.1 Kolmogorov-Smirnov Test Results

As per the Methodology section, the first step is to run the KS test. When comparing the distributions for arrests of white individuals to black individuals, we get a positive D estimate of approximately 0.135. This estimate can be found in Table 1 and is the maximum distance between the two curves in the lower severity range, so it gives little to no information regarding the disparity and is, therefore, not important apart from being non-zero. The more important estimate is the p-value of 2.2×10^{-16}, essentially 0. This means that the distributions are significantly different between 0 and 30 grams. When looking at the higher severity, between 30 and 100 grams, D is 0.047, a much smaller maximum difference. But again, I care about the p-value to determine if the more sever distributions are statistically different. The p-value for this range is 0.49 and therefore, which tells us the distributions are similar enough to be statistically identical. These outcomes are in line with my hypothesis and motivate the next section of this paper.

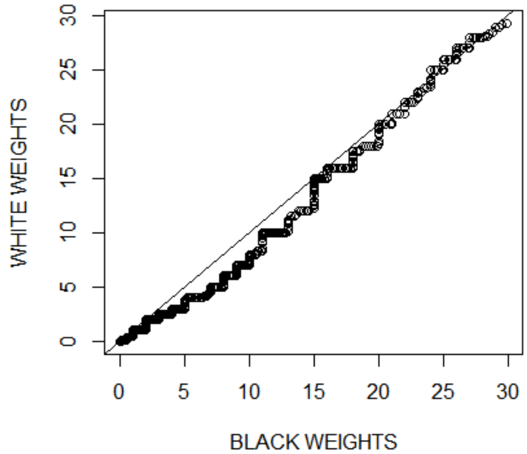
As a follow up to this test, I also create a quantile-quantile plot, which can be used to eyeball whether two datasets follow the same distribution. If they do, the plot creates relatively straight line, diagonally, across the plot box. This plot is shown in Figure 7 and provides further evidence that the distributions differ on the lower end of the distribution, but less so on the upper end. There is too much curvature to say these follow the same distribution. In the figure, "WEIGHTS" refers to the approximate weight of marijuana in their possession.

5.2 Linear Regression Results

As is detailed in the previous section, I model the affect of race on arrest rates by running a linear regression where arrest rates is the outcome and Race $\times$ Quantity is the main regressor. This provides the estimated difference in arrests rates due to being in race group r at quantity level q. I then calculate the difference in this disparity at each contraband level using equations (a) through (c) and determine if there is evidence of unequal treatment at lower levels.

The results for equation (1) are reported in Table 2. Here, the omitted dummy variable is that of Black individuals in Quantity region 1. Therefore, this is our estimate of the less than 2.5 grams quantity black arrest rate, and thus γ_1^{B1} is essentially zero. It is approximately 31 arrests/100,000 population. This

Figure 7



is significant at 99.999% level. The estimate for γ_1^{W1} is -28.9, or there are nearly 29 fewer marijuana arrests per 100,000 population of white people with less than 2.5 grams in their possession. The estimated γ_1^{B4} is -21.2 and γ_1^{W4} is -30.2. Given the base level is γ_1^{B1}, β_1^1 is simply 28.9 (I round up to 30), or the difference between γ_1^{B1} and γ_1^{W1}. Taking the difference between γ_1^{B4} and γ_1^{W4} (in absolute value, since both deviate from γ_1^{B1} in the negative direction), we find $\beta_1^4 = 9$. Now it is straight forward to calculate the differential in the disparity:

$$\beta_1^1 - \underbrace{\beta_1^4}_{\text{Statistical}} = \underbrace{\widetilde{\beta}_1}_{\text{Taste-based}} \tag{c}$$

$$30 - 9 = 21$$

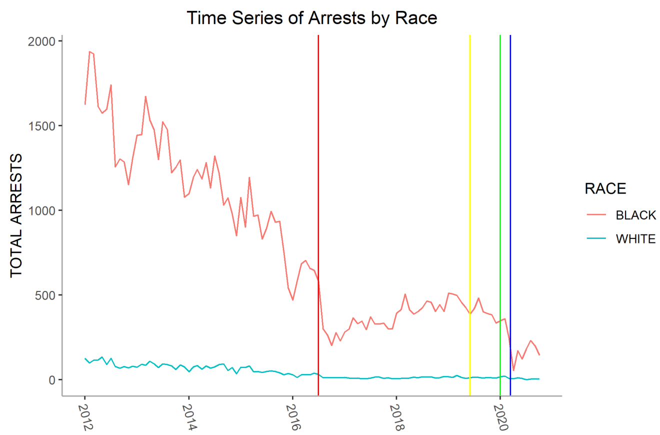
Thus, $\widetilde{\beta}_1 = 21$ and is consistent with my hypothesis because it shows that the disparity in arrest rates by race is more than two times higher for smaller quantities. The estimates for these values from equation (2) are almost exactly the same, except the intercept is 46. This, however, does not affect the differential of the disparity estimates, only the level of the disparity. Therefore, $\widetilde{\beta}_1$ is still 21.

5.3 Interrupted Time Series Results

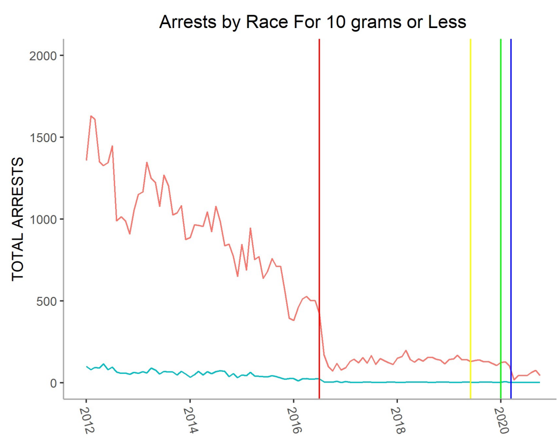
Figure 8 includes four panels, detailing the time series of arrests by race to visualize the disparity in overall arrests.

Figure 8

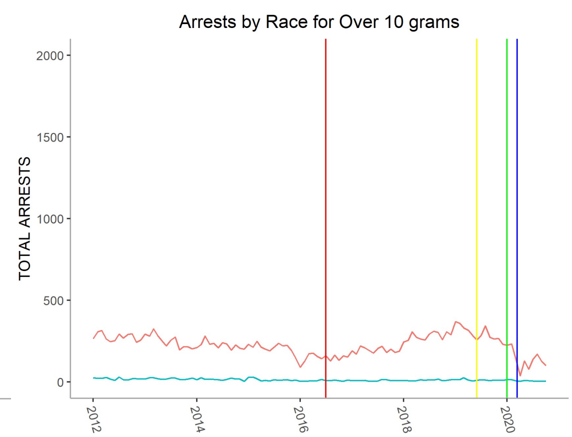
(a)



(b)



(c)



Looking at these figures, it is clear that, prior to decriminalization, there was a downward trend in overall black arrests for marijuana possession; this was largely driven by decreases in arrest rates at lower quantities. At the time of decriminalization there is a stark drop in arrest rates that leads to a new level of arrests, but also to a different slope of arrest rates over the following years. There are a couple other noticeable drops ion monthly arrest rates between 2012-2016, but they both appear to be temporary and leave the overall trend relatively unaffected. In the overall time series in Figure 3, there is a larger downward slope going from mid 2015 to the end of 2015. I believe this is due to the change in stop and frisk policy that occurred over the course of several months, but it appears to by only lead to a temporary drop in marijuana arrests.[13]

For panel 8c, there is seemingly no drop in the monthly arrest rate at the time of decriminalization; if there is a level change in the disparity, it is quite small, though may be slightly more pronounced at the day frequency when I can more clearly estimate the level before and after the policy change. It does appear to be followed by an increase in the black arrest rates for higher quantities of marijuana and, therefore, a change in the slope of the disparity. Since the plot of arrest rates does not give the statistical significance of level and trend changes, I estimate the ITS under each possible scenario: (1) both trend and level are affected by the policy, (2) only the level is changed, (3) only the slope is changed. I then use the estimates of these models to determine which best describes the effect of the policy change in the arrest rate disparity and run this model for each race group.

The results presented in Table 3 through 5 show that the effect of decriminalization likely, even if to a small degree, had an effect on the level and slope of each group. Therefore, I use ITS 1 to estimate the results for Table 6. The first thing to take away from these results is that the decriminalization policy appears to have no affect on white arrest rates for possession of less than 10 grams of marijuana. For black arrest rates, the policy change leads to a decrease in the level by approximately 0.63 or a decrease of 63 arrests per 1000 population. Therefore, the disparity here sees a large decrease (by 63 arrests per 1000 pop). There is also a resulting positive change in the slope, increasing the trend by about 10 percent. This makes sense because the number of arrests are quite low after the policy change, but means that decriminalization in Chicago did result in a flatter downward trend. For high quantities, decriminalization is associated with a decrease in black arrests by 5.5 per 1000 population and for white arrests a decrease in arrests by 2 per 1000 pop. Therefore, the disparity decreases by 3 arrests per 1000 population. These changes are much smaller, which is what we would expect because the laws changed such that up to 10 grams results in a fine, but no arrest, while over 10 grams is still a crime in this period.

[13] I describe this policy shift in 2.1

A more interesting result at higher quantities is that the trend increase enough after decriminalization to become positive. I posit that this affect is due to resource reallocation. Police resources are no longer dedicated as much to arresting and stopping individuals who much have small amounts of marijuana on their person. Instead, they can use their time to focus on more severe offenses. If they care about getting drugs off of the street, they will then focus more time on arresting individuals with large amounts of marijuana, rather than small. This leads to more time focused on stopping gang and cartel related drug crimes, rather than average people with a joint on them for later. Additionally, there is less money allocated toward sentencing and jailing of these individuals that can be used for higher severity offenses. I would like to point out that this trend shift is more pronounced for black arrest rates than white arrest rates and may indicate that this higher quantity increase in enforcement may disproportionately affect minorities. Looking at Figure 8a, it appears this upward trend in black arrests could have kept increasing to the pre-policy change levels. However, this does not occur. It is possible that the passing of legalization in IL changed the overall trend enough to keep this from occurring. I plan to analyze the policy change here in future research and determine if this is the case.

5.4 Robustness and Heterogeneity

The main issue with an Interrupted Time Series approach is the presence of partial or serial autocorrelation. It is often present in the model when one or more important variables are omitted. I plotted the residuals for my data, it does not appear that this is too much of a concern based on the plotted residuals for the black arrest rate models; however there is a bit more of a concern with regards to ITS 1 for white arrests as is seen in Figure 10. Unfortunately, with this data, I do not have a way of dealing with this issue at this time. It could lead to some bias in the estimated outcome of the ITS models.

Figure 11a shows the incidence of arrests of black people for possession of marijuana in Chicago. The black colored region is the rest of cook county, outside of CPD jurisdiction. Alternatively, Figure 11b shows the incidence of arrests of white people for possession of marijuana in Chicago. The scales for these figures differ, so this is meant to show where the majority of arrests are occurring for each race, though the highest number of arrests in a particular district are much higher for black individuals, at almost 10,000. That of white individuals is 288. It is notable that the zip codes with higher frequencies occur mostly to the south east portion of Chicago for black arrests, with those of white occurring more toward the northern

Figure 9
Plotted Residual for Black Arrests

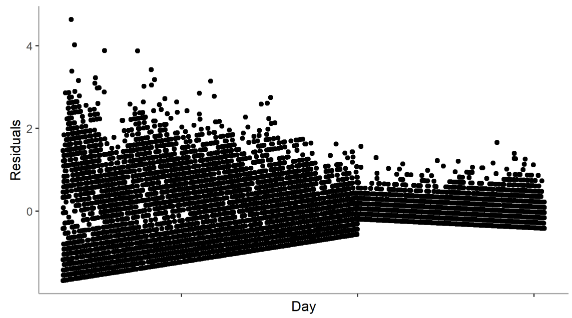
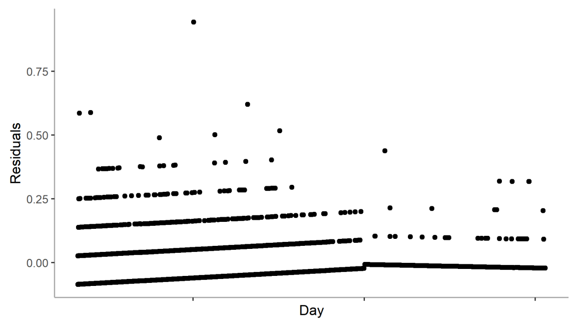


Figure 10
Plotted Residual for White Arrests



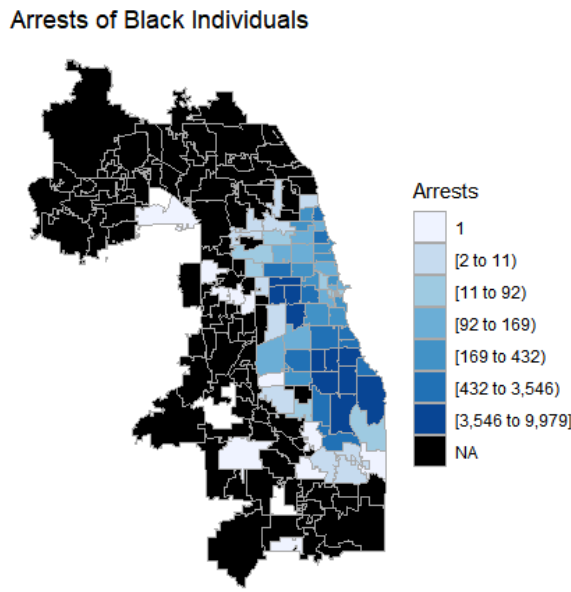
districts of the city. Also, note that many of the blackened districts are outside of CPD jurisdiction, though not all of them. Within their jurisdiction, some districts do have very few or zero arrests, especially for white arrests.

Figure 12 shows the arrests per population of each zip code for possession of marijuana in Chicago.[14]This map specifically details the arrests within the city limits of Chicago, rather than the whole Chicago Metro area. The district in gray is the Chicago O'Hare International airport, so it has a population of 0. Panel 13a shows all of the marijuana arrests per total population of the district. Panel 13b shows the marijuana arrests of all white people per population within each zip code district. Panels 13c and 13d show the same information for black and Hispanic peoples, respectively.[15] The large gray district is gray because, although there are arrests in it, there is a 0 population as it is the Chicago O'Hare International Airport.

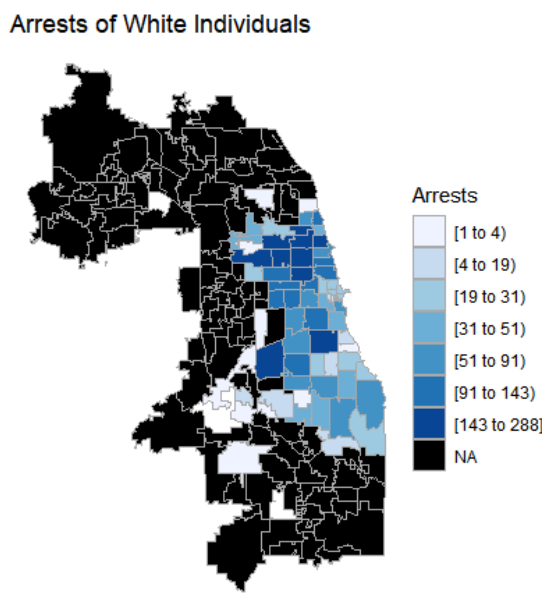
[14]The population by Zip code comes from 2018 census provided by the U.S. Census Bureau.
[15]Here, Hispanic is the sum of black and white Hispanic individuals.

Figure 11

(a)


Arrests of Black Individuals
Arrests
1
[2 to 11)
[11 to 92)
[92 to 169)
[169 to 432)
[432 to 3,546)
[3,546 to 9,979]
NA

(b)


Arrests of White Individuals
Arrests
[1 to 4)
[4 to 19)
[19 to 31)
[31 to 51)
[51 to 91)
[91 to 143)
[143 to 288]
NA

Looking at this figure, it is strikingly noticeable that much of the denser zip codes. Keep in mind that this shows the arrests of each race per total population of the district, not the population by race. It is also clear that there are certain districts that tend to have higher arrest rates for marijuana possession than others across all races. White arrest rates are the most evenly dispersed of all three races. Keep in mind that Chicago is approximately 30% white, 30% black, and 30% Hispanic, according to the U.S. Census Bureau.

6 Conclusion

For decades, researchers, social activists, and the media have brought attention to racial disparities across a multitude of platforms, from wage disparities to the ability to take out a mortgage. In recent years, this attention has focused more closely on how the police interact with minority citizens. There has been a surge in protests of police brutality and prejudice against minorities. Though it is important the public be active in keeping others safe and playing a part in ensuring equity to hold policy makers and law enforcement accountable, it is also necessary to first have all of the information to make a positive change. Much of the literature on racial disparities provide evidence of racial discrimination in the criminal justice system[16]. Others find little or no evidence of racial discrimination[17]. Though there are mixed results when trying to determine if there is racial discrimination, there is still a racial disparity present in stop rates, arrest rates, sentencing and parole, etc. that has not been fully explained by the characteristics of the individual or crime committed. Determining how much of the racial disparity is due to discrimination is essential in order to properly allocate government resources to law enforcement and to reduce costs to society of unequal punishment for crimes.

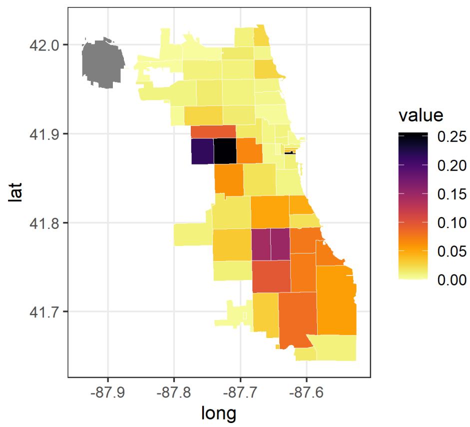
This paper uses density function comparison techniques to illustrate how the arrest rate disparity is determined by the prevalence of racial discrimination. It uses data from the Chicago police department on the severity of contraband found leading to arrest, which has not been used in prior research. Using severity allows me to run a heterogeneity analysis to see the affect of leniency at different levels of severity. Officers are less likely to show leniency to any driver for a more serious crime, but they may show leniency for less serious crimes. Thus, if discrimination were to enter into the arrest decision, we would see this at

[16] Mustard 2001, Arvanites and Asher 2006, Abrams et al. 2012, Alesina and La Ferrara 2014, West 2018, Pierson et al. 2019

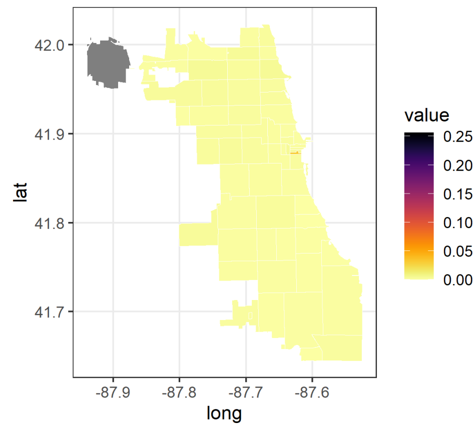
[17] Grogger and Ridgeway 2006, Anwar and Fang 2012

Figure 12

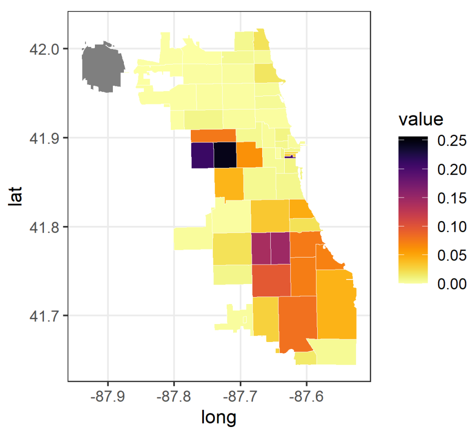
Figure 13
Arrest Rates by Zip Code



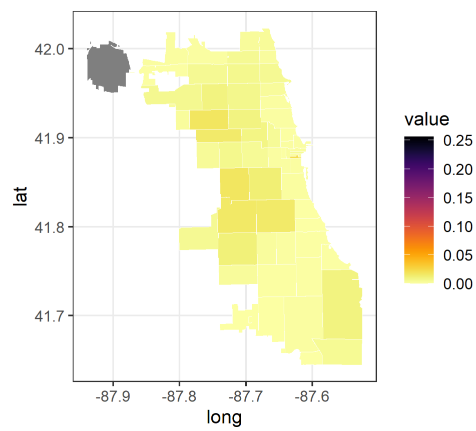
(a) All Arrests per Zip Pop



(b) White Arrests per Zip Pop



(c) Black Arrests per Zip Pop



(d) Hispanic Arrests per Zip Pop

lower levels, but not higher levels of severity. Therefore, the racial disparity in arrests should smaller at higher levels. The results of the model estimates is consistent with this type of behavior causing a significant portion of the racial disparity in arrest rates.

Based on this outcome, I use an Interrupting Time Series model to estimate the effects of marijuana decriminalization, that occurred in Illinois in 2016. These results imply that decriminalization decreases the arrest rate disparity by 0.63 arrests per 100,000 population for lower quantities with only a very small effect on higher quantity arrests (as is expected)in the city of Chicago; however, it leads to an increase in the trend of the disparity over time in the higher quantities that may only have failed to continue past 2019 due to legalization, a question I would like to examine further in future research. The effect on the disparity in the lower range is larger than estimates in previous research, but it is important to recall that this is partially due to it being only for arrests of less than 10 grams of marijuana and partially could be due to this data being for the city of Chicago, where arrests of black people tend to be around 75% of overall arrests. The estimate for all arrests is very similar to the estimates seen in other research and implies an approximately 0.36 decline in the arrest rate disparity.[18].

The policy implications of the results presented in this paper are that the government should allow laws to evolve in a way the more equitably penalizes citizens for their crimes. Relaxing laws for crimes that cause little or no harm to others, such as marijuana use, can decrease the amount of racial discrimination within the justice system. This is directly beneficial to minority populations who no longer need to fear unequal treatment for these crimes. Additionally, it means the government can save on costs to imposing such laws and to imprisonment and detainment of people who break them. This allows police to spend more money and time on enforcing laws for more serious crimes, such as trafficking schedule one drugs. The result is a more efficient and effective police force and a more fair justice system.

The results of these tests provide a more accurate picture of the leniency officers apply based on driver's race, and provide evidence for the prevalence of taste-based discrimination. Using this idea to analyze the effects of

The policy implications of this would be that relaxation of minor crime laws can decrease the racial disparity in arrests and allow police department funding to be reallocated toward more severe crime

[18]These can be seen in 6

enforcement and increased effectiveness.

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7 Tables

Table 1
Results of Kolmogorov-Smirnov Test

	D	p-value
Less than 10g	0.12282	2.2×10^{-16}
Less Than 30g	0.135	1.487×10^{-5}
10g to 30g	0.0755	0.1713
30g to 100g	0.047	0.4888
100g to 300g	0.118	0.0297
300g to 500g	0.12674	0.4643

Notes: This table reports the estimated D (maximum difference) and p-value for the Kolmogorov-Smirnov tests. The p-value is what we care about, here. The data for this table comes from the Chicago Police Department and is not available to the public. It includes all marijuana arrests in Chicago from Jan 2012-Oct 2020.

Table 2
Results of Linear Models

	(1)	(2)
Intercept	**30.979*** **	**45.8403*** **
	(1.469)	(8.468)
Black with 2.5-10g	**6.287** **	**6.287** *
	(2.077)	(3.095)
Black with 10-30g	**−12.313*** **	**−12.313*** **
	(2.077)	(2.240)
Black with >= 30g	**−21.199*** **	**−21.199*** **
	(2.077)	(2.375)
White with < 2.5g	**−28.882*** **	**−29.600*** **
	(2.125)	(2.271)
White with 2.5-10g	**−29.398*** **	**−30.616*** **
	(2.142)	(2.290)
White with 10-30g	**−30.273*** **	**−30.745*** **
	(2.097)	(2.311)
White with > 30g	**−30.227*** **	**−30.433*** **
	(2.092)	(2.317)
R^2	.456	.623
Adj. R^2	.452	.563
N	820	
Statistic		10.777
P Value		.000
DF Resid.		707.000

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: Regression output of equation 1, 2, and 3. This estimation uses Chicago PD data aggregated to the appropriate level for arrest rates in each model.

Table 3
Results of Interrupted Time Series

	(ITS 1)	(ITS 2)	(ITS 3)
Intercept	0.59989^{***}	0.68101^{***}	0.50351^{***}
	(0.01754)	(0.01654)	(0.01445)
Day	-0.00039^{***}	-0.00030^{***}	-0.00048^{***}
	(0.00002)	(0.00002)	(0.00002)
Decrim	-0.29498^{***}	-0.11017^{***}	
	(0.03069)	(0.02750)	
Day × Decrim	0.00058^{***}		0.00039^{***}
	(0.00004)		(0.00004)
R^2	0.12209	0.11041	0.11591
Adj. R^2	0.12189	0.11028	0.11577
Num. obs.	13113	13113	13113

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: Interrupted time series output of ITS 1, 2, and 3. This estimation uses Chicago PD data aggregated to the appropriate level for arrest rates in each model. Changes in the arrest rate can be interpreted as a change in the number of arrests per 100,000 population.

Table 4
Results of Interrupted Time Series Quantity 10g or Less

	(ITS 1)	(ITS 2)	(ITS 3)
Intercept	0.77867^{***}	0.85226^{***}	0.64579^{***}
	(0.02644)	(0.02524)	(0.02263)
Day	-0.00061^{***}	-0.00052^{***}	-0.00072^{***}
	(0.00003)	(0.00002)	(0.00002)
Decrim	-0.48080^{***}	-0.24573^{***}	
	(0.05029)	(0.04299)	
Day × Decrim	0.00066^{***}		0.00029^{***}
	(0.00007)		(0.00006)
R^2	0.23227	0.22367	0.22230
Adj. R^2	0.23194	0.22345	0.22208
Num. obs.	7043	7043	7043

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$; $^{\#}p < 0.1$

Notes: Interrupted time series output of ITS 1, 2, and 3 for possession of 10 grams or less of marijuana. This estimation uses Chicago PD data aggregated to the appropriate level for arrest rates in each model. Changes in the arrest rate can be interpreted as a change in the number of arrests per 100,000 population.

Table 5
Results of Interrupted Time Series more than Quantity 10g

	(ITS 1)	(ITS 2)	(ITS 3)
Intercept	0.36051***	0.42768***	0.34243***
	(0.01115)	(0.01045)	(0.00874)
Day	−0.00009***	−0.00002	−0.00011***
	(0.00001)	(0.00001)	(0.00001)
Decrim	−0.04695**	0.05535**	
	(0.01796)	(0.01700)	
Day × Decrim	0.00039***		0.00036***
	(0.00003)		(0.00002)
R^2	0.03991	0.00241	0.03883
Adj. R^2	0.03944	0.00208	0.03851
Num. obs.	6070	6070	6070

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: Interrupted time series output of ITS 1, 2, and 3 for possession of more than 10 grams of marijuana. This estimation uses Chicago PD data aggregated to the appropriate level for arrest rates in each model. Changes in the arrest rate can be interpreted as a change in the number of arrests per 100,000 population.

Table 6
Results of ITS using Best Model for Each Race-Quantity Group

	Black	White	Black Low	White Low	Black High	White High
(Intercept)	0.68827***	0.13409***	0.93712***	0.13372***	0.38826***	0.13463***
	(0.01895)	(0.00413)	(0.01893)	(0.00531)	(0.01175)	(0.00519)
Day	−0.00067***	−0.00004***	−0.00119***	−0.00005***	−0.00015***	−0.00000
	(0.00002)	(0.00000)	(0.00002)	(0.00001)	(0.00001)	(0.00000)
Decrim	−0.36748***	−0.01558	−0.62828***	−0.00411	−0.05466**	−0.02083*
	(0.03135)	(0.01024)	(0.03260)	(0.01926)	(0.01872)	(0.00901)
Interact	0.00088***	0.00005***	0.00124***	0.00004	0.00050***	0.00003*
	(0.00004)	(0.00002)	(0.00005)	(0.00003)	(0.00003)	(0.00001)
R^2	0.28361	0.05399	0.72571	0.06691	0.06918	0.00897
Adj. R^2	0.28340	0.05302	0.72555	0.06546	0.06863	0.00600
Num. obs.	10170	2943	5105	1938	5065	1005

$^{***}p < 0.001$; $^{**}p < 0.01$; $^{*}p < 0.05$

Notes: Interrupted time series output of ITS 1 for each race-quantity group(all, 10g or less, more than 10 grams, for each all, black, and white race groups). ITS 1 appears the best model for each quantity group, so I use it to estimate the results in this table. This estimation uses Chicago PD data aggregated to the appropriate level for arrest rates in each model. Changes in the arrest rate can be interpreted as a change in the number of arrests per 100,000 population.