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Adult Drug Treatment Courts and Community-Level Drug Possession Arrests

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Abstract

Though the literature largely recognizes adult drug treatment courts (ADCs) as beneficial to participants, with lower rates of recidivism and drug use, the question remains of how ADCs impact communities and how other institutions (e.g., law enforcement) react to their presence. This study extends previous work estimating higher arrests associated with ADCs, particularly for crimes involving higher degrees of law enforcement discretion. Results indicate lower drug possession arrest rates for White residents in rural communities, and higher in urban areas, generally, but especially for Black citizens. Though the exact source of these changes has yet to be determined, current analysis indicates larger effect sizes for arrests scaled per officer, as compared to per population, pointing toward changes in law enforcement behavior.

Keywords

drug courts; law enforcement behavior; police discretion; econometrics

Introduction

Miami-Dade County created the first adult drug treatment court (ADC) as a response to the War on Drugs, tough-on-crime era of mass policing and incarceration (for a detailed history and description see Noia et al., 2018). This flooded court dockets with low-level drug arrests (Rossman, Roman, Zweig, Rempel, Lindquist, Markman, et al., 2011a). The ADC model modifies court operations from traditional adversarial and punitive structures toward cooperation and service provision. Externally, ADCs collaborate with cross-sector organizations (e.g., service providers), under the premise of addressing conditions (e.g., substance use disorder; SUD) antecedent to crime (NADCP, 2018a).

The bulk of research evaluating ADCs examines individual-level outcomes. These studies indicate lower rates of recidivism and drug use, especially for graduates (GAO, 2005;

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Rossman et al., 2011a; Sevigny et al., 2013; Shaffer, 2011). The few randomized control trials offer somewhat mixed results, with generally lower re-offending rates for participants, and no effects for public health outcomes like drug overdose deaths (Gottfredson & Exum, 2002; Gottfredson et al., 2005, 2006; Kearley & Gottfredson, 2020; Kearley et al., 2019; Mackin et al., 2009). The participant unit-of-analysis, though, misses important contextual information, such as conditions in the community that influence ADC implementation, operation, and success. Further, courts embody an explicit community-level mandate toward public safety (NADCP, 2018a).

Efforts assessing ADC impact on communities do not return such encouraging estimates. Recent work looking at effects on community-level arrests found increases in low-level offenses, particularly drug possession arrests (Lilley, 2017; Lilley et al., 2020), with the greatest increases found in arrests of minority residents (Lilley et al., 2019). Authors cited changes in law enforcement behavior (e.g., net widening) as a potential mechanism.

Primarily, this paper demonstrates utility of the stacked event study methodology in criminal justice and policy/program analysis contexts. Moreover, it adds to the criminal justice literature by evaluating a widely adopted program on an understudied unit-of-analysis, communities, improving our understanding of how ADCs function, and pointing toward improved operations. Finally, results provide crucial information about the complex contextual factors of this type of program and how related institutions can help or hinder each other's operations, such as law enforcement changing their behavior relative to ADC implementation.

Literature Review

Research evaluating ADCs almost universally focuses on the participant unit-of-analysis. Results for ADCs generally agree on positive effects, with lower recidivism rates and incidence of drug relapse (GAO, 2005; Rossman et al., 2011a, 2011b). Several meta-analyses cover these, also generally agreeing that ADCs achieve their intended purpose (Downey & Roman, 2010; Latimer & Chretien, 2006; Lowenkamp et al., 2005; Sevigny et al., 2013; Shaffer, 2011). The few randomized control trials (RCTs) return somewhat mixed results. For example, analyses of a 1997 RCT of the Baltimore City Drug Treatment Court found initial reductions in relevant outcomes early on (Banks & Gottfredson, 2003; Gottfredson & Exum, 2002; Gottfredson et al., 2003, 2005), mainly no effects in longer-term analyses, no impact on health outcomes (Kearley et al., 2019), and back to lower rates of arrest on a 15-year timeline (Kearley & Gottfredson, 2020).

Participant-level research, though, provides intermediate outcome analysis if our concern involves community impact—it only demonstrates effectiveness for participants, generally participants who graduate—potentially missing key elements that might influence ADCs' impact on communities (e.g., changes in law enforcement behavior).

Scholars recently began exploring ADC outcomes at the community level. Lilley (2013) found an increase in known offenses (see discussion below regarding crime data sources) relative to ADC implementation, arguing the potential for participants who do not graduate accounting for more of an increase in crime than graduates a reduction; especially, the author argued, if dropouts remain in the community without some type of supervision (citing Belenko, 1999). Other studies indicate increases in drug arrests and low-level offenses in which law enforcement officers have more discretion (Lilley, 2017; Lilley et al., 2020), especially impacting minority citizens (Lilley et al., 2019).

The current paper examined the relationship between ADCs and drug possession arrests, which represent the portion of crime known solely through law enforcement efforts. Though this measure includes information about actual crime in the community, not all arrests indicate a crime, per se, especially offenses with a wide degree of police discretion (i.e., *mala prohibita* crimes; see Sekhon, 2011). Figure 1 displays a construction of crime data sources. Considering the totality of crime, "actual crime," some portion is known by reporting agencies, "known offenses." A portion of known offenses come from community reporting and another from police work, and a portion of offenses known through both community reporting and law enforcement activity lead to an arrest. Notice, however, that a sub-section of arrests of crimes detected by law enforcement exists outside of the actual crime area. This represents the question at hand, whether police behavior might influence crime by enforcing high-discretion offenses like drug possession (Brunson & Miller, 2006; Ericson, 1993).

Present Study

This study explored the relationship between adult drug treatment courts and community-level drug possession arrests and, given any relative difference, whether they might be due to changes in law enforcement behavior. Toward this end, I estimated the magnitude and direction of dynamic treatment effects that adult drug treatment courts have on county-level drug possession arrests. This program has diffused across US jurisdictions such that, currently, nearly every county either features an ADC or is covered by one from an adjacent jurisdiction (National Drug Court Resource Center, 2021). Since this program affects so many lives—researchers estimate participation over 100,000 annually (e.g., Marlowe et al., 2016)—and commands a substantial share of public resources, understanding how ADCs impact communities amounts to a critical research question. The disparities between individual- and community-level analyses also call for reconciliation. Additionally, institutions in the criminal legal system interact in complex and nuanced ways that either help or hinder each other's efforts toward desired outcomes like improved public safety. Understanding such relationships will point toward ways to improve these relationships and, thus, public safety. Finally, estimating community-level outcomes for programs like ADCs presents several issues of validity and robustness. Toward this end, the current study demonstrates the utility of a stacked event study design to better evaluate this level of performance.

This work built upon previous efforts by increasing the timeline (1990–2018), including more jurisdictions, applying state-of-the-art statistical techniques, and exploring more constructions of outcomes (i.e., analyses by population group, scaled by both general and law enforcement populations). I performed dynamic analyses (i.e., event studies, equation (3) from Supplemental Appendix B) on a unique ADC dataset, arrest data from the Uniform

Crime Reporting Program, and relevant control data. These analyses were conducted on five population groups: 2,500 to 9,999 (2.5k), 10,000 to 24,999 (10k), 25,000 to 49,999 (25k), 50,000 to 99,999 (50k), and 100,000 and above (100k).

There are several reasons a priori to believe a connection exists between ADCs and drug possession arrests, albeit difficult to predict which direction. With the bulk of individual-level research demonstrating lower recidivism and drug relapse rates for ADC participants, one might expect lower possession arrests (GAO, 2005; Rossman et al., 2011a, 2011b). Programs like this, however, do not operate in a vacuum. The possibility also exists, as proposed by previous work in this vein, that other actors in the criminal legal system may change their behavior in the presence of ADCs (Gross, 2010; Lilley, 2017; Lilley et al., 2019, 2020). One suggested behavior change comes from law enforcement possibly using their discretion to increase low-level arrests.

Some research has also suggested the potential for ADC non-graduates to reoffend at a higher rate that may counterbalance the lower rates observed with graduates (Lilley, 2013). The literature has yet to establish whether ADC non-graduates show higher or lower rates of recidivism relative to the broader system-involved population. Jewell et al. (2017) found non-graduates recidivate at higher rates than those who declined to participate. Others have suggested some who end up in ADCs do not have serious drug issues, potentially ending up worse off than if they had never participated (DeMatteo et al., 2009). Other work (e.g., Gottfredson et al., 2003) indicated individuals who do not graduate show lower recidivism than non-participants.

Thus, we can assume some mix of individual-level outcomes that might influence community crime relative to ADC implementation: those that benefit from ADCs lowering rates of arrest on one side, and those that might be worse off for participating increasing it on the other. The question, by this logic, amounts to these competing internal forces combined with external influences such as police behavior. Ergo, this study made no prediction of whether ADC implementation will be associated with higher or lower drug possession arrest rates.

Data

To evaluate the relationship between ADCs and drug possession arrests, I used a unique ADC dataset built by expanding upon information previously available publicly, arrest data from the Uniform Crime Reporting Program’s summary reports, and relevant control variables. See Supplemental Appendix C for explanation of all data sources and processing procedures.

Outcomes.—This study used arrest data from the FBI’s Uniform Crime Reporting (UCR) summary reporting program, which Jacob Kaplan concatenated into annual files (Kaplan, 2021b). UCR data come with worries about measurement error (see Boylan, 2018; Loftin & McDowall, 2010). To deal with these, I limited data to those agencies reporting all 12 months per year for the entire period of each stack (see Supplemental Appendix B) and cover a minimum population at any point in the study. This population figure varies depending on sub-analysis. I also kept only agencies that enter the dataset for all years in each stack, creating a sample fully balanced in calendar years (the stack process also balances data in relative years; see Supplemental Appendix B).

Agency-level observations were aggregated to the county level and constructed into two different rates: arrests per 1,000 citizens and per 1,000 law enforcement officers. Analyses were performed on these rates for drug possession arrests of Black, White, and all individuals. Scaling by population followed traditional research on crime—that using officers served a unique purpose. Previous work posited increases in possession arrests result from changes in law enforcement behavior. If this is the case, then it is likely correlations between ADC and possessions per 1,000 officers will return larger coefficients than rates per 1,000 citizens, especially in cases of increased arrests scaled by population.

Independent variable.—I built upon data previously offered publicly by the National Drug Court Resource Center (National Drug Court Resource Center, 2018). Their data presented information gained from a survey of court administrators throughout the US, which included name and type of court, primary county of jurisdiction, and some implementation dates. I expanded this to include all counties each court covers and added more implementation dates. As hybrid DWI/drug treatment courts (HYBs) evolved from adult drug treatment courts, cover many of the same individuals, and involve nearly identical processes, this study combines both types of courts for analysis (with the term “ADC” referring to both). I excluded any county indicating the operation of an ADC but no implementation date.

To conform to the empirical strategy, the primary independent variable used for analysis indicates if any ADC operates in a given county-year or not. This misses some information, such as whether additional courts offer more or less impact, the impact of court capacity, or if some courts shut down, but fit the most robust analytical techniques with available information.

A note is also necessary regarding jurisdiction. Some urban counties contain several ADCs, while some rural courts cover several counties. Analyses included a binary covariate indicating whether a court covers multiple counties to address this.

Covariates and other variables.—Though the empirical strategy (described below briefly and in more detail in Supplemental Appendix B) implicitly controls for many temporal and geographical factors that might influence the relationship between ADCs and arrests, I also included control variables along these lines. For instance, though analysis includes arrest rates per population, population is included as a covariate. Population density[1] serves as a proxy measure of access to services (Allard, 2004). Further, the study included covariates commonly associated with crime rates and likely to influence the crime-ADC relationship: percentages of those aged 15 to 24, male, and White (NIH | SEER, 2021); and unemployment rates (Bureau of Labor Statistics, 2021). As a measure of the local construction of issues like crime and substance use, analysis also included a temporal-proximity weighted measure of the percentage of Republican presidential votes at

1. $Population_{ct}$ / $CountySquareMiles_{c}$

the county level (Stavick & Ross, 2020). Data from the Law Enforcement Officers Assaulted or Killed dataset (Kaplan, 2021a) were also included, converted to a rate of officers per 1,000 population. These law enforcement data were also used to calculate arrest rates per 1,000 officers mentioned above. All control variables were log transformed to bring them closer to normal distributions, which aids in data preprocessing (matching) and analysis.

Empirical Strategy

As described in detail in the Supplemental Appendix B and briefly here, analyses included dynamic fixed-effects identification on a specially constructed dataset (stacked event study; Cengiz et al., 2019). Research at the community unit-of-analysis presents the potential for confounding and biasing factors. For instance, local efforts to address crime (or its antecedents) other than ADCs might influence the outcomes being measured (confounding variables), particularly if they operate concurrently, driving spurious interpretation. Contextual elements may also influence the relationship between ADCs and arrests, biasing estimates (see, generally, Angrist & Pischke, 2009).

To assess the relationship between ADCs and drug possession arrests at the county level, analyses were performed on a dataset constructed of several sub-experiments. Each of these (termed "stacks") consists of counties that implemented an ADC in a target year and those that did not for that year, 5 years prior, and 5 years afterward. These sub-experiments were then appended on top of each other (stacked, where the method gets its name) for analysis. The resulting dataset provides more of an "apples-to-apples" comparison than traditional longitudinal methods, particularly after performing nearest-neighbor matching relative to outcome and control variables (see Supplemental Appendix C for a full description of matching methods). Further, the strategy avoids violations of the assumptions associated with dynamic fixed-effects analysis (e.g., homogenous treatment effects; Sun & Abraham, 2021).

This strategy limited the number of years included, since dataset construction required a cushion of 5 years before and after the target implementation year of each stack. Though years 1990 through 2018 were included, counties that implement ADCs are limited to 1995 to 2013. The limitation does not, however, present cause for concern. Prior to 1995, ADCs numbered in the dozens, whereas they numbered over 1,000 in the 2000s. Further, implementations of new ADCs decelerated substantially after their peak in 2007 (see Figure 4 below).

Since this specification created a large amount of information, I present below a linear combination of years 1 to 5 after implementation (using Stata's lincom command), rather than the traditional event study graphs, though these are also included in Supplemental Appendix A.

Results

Descriptive Statistics

Table 1 shows descriptive statistics for law enforcement personnel, drug possession arrests per 1,000 population and per 1,000 law enforcement officers, and socio-economic variables.

Though many of the variables show a statistically significant difference between counties that adopted an ADC and those that do not, standard differences[2] appear nominal. Population and percent of the population between ages 15 and 24 show the highest difference—0.19 and 0.12 *SD*, respectively. Summary statistics represent those for the analysis sample over the entire study period, 1990 to 2018, excluding any overlapping county-years between stacks.

Figure 2 displays drug arrest trends per 1,000 population over time between counties that ever adopted an ADC and those that never do. I also included aggregate number of ADCs on the right axis. Note that trends, and ADC counts, came from the universe of data, not the analysis sample. Both groups exhibit roughly similar time trends with noticeable divergences beginning in the mid-1990s—ADC counties showing larger increases in arrest rates. Interestingly, and as our first clue into the relationship between ADCs and arrests, these differences flatten out for arrests of total and White individuals in the late 2000s but not as much for Black residents.

Table 2 provides counts of ADCs, hybrid DWI/drug courts, and their sum for all known (as of 2018) and those included in the current analysis sample. Figure 3 reports implementation trends and cumulative number of ADCs over time for both the population of ADCs and those included in the analysis sample. Both exhibit similar trends, with generally increasing new courts implemented up to a peak in 2007 and a deceleration from there. Note that the x-axes are on different scales, with the population graph including years 1989–2018 but the sample limited, by construction (see Appendix B), to 1995 to 2013. As of 2018, roughly 1,700 ADCs operated throughout the US. These figures refer to individual courts, not counties or jurisdictions covered (see conversation above regarding issues with jurisdictions and ADCs).

Core Analysis

Table 3 reports linear combinations of coefficients for relative bins representing 1 to 5 years after ADC implementation, taken from equation (3) in Supplemental Appendix B (see Supplemental Appendix A for complete event study graphs). The 25k and 50k population groups showed no significant results. 2.5k returned one significant coefficient ($p = .056$), if we use a 90% confidence standard, indicating a bit over 25% fewer possession arrests of White citizens per 1,000 officers. While this percentage appears high, keep in mind the small population group (see counterfactual analysis below for discussion of change in the actual number of arrests). The 100k group returned a positive relationship (10.19%) between ADCs and arrests of Black individuals per 1,000 citizens, and a larger such correlation (11.52%) per 1,000 police officers. Total possession arrests in this population group also presented a significant relationship with ADCs (6.61%) though arrests of White citizens did not.

Interesting results came from the 10k group. On one hand, both possession arrests of total and White individuals per 1,000 officers returned highly significant ($p = .008$ and $p = .006$, respectively) and substantial negative coefficients (−13.67% and −14.36%). On the other, the

2. $\frac{\mu_{ADC} - \mu_{noADC}}{\sqrt{s_{ADC}^2 + s_{noADC}^2}}$

event studies included in Supplemental Appendix A, and reported below in Figure 4, showed positive pre-trends for arrests of Black residents and ADC implementation whether scaled by population or officers. It appears higher rates of arrests of minorities predicted ADC implementation for this population group, but White citizens reap the rewards. Considering this set of analyses as a whole, a pattern emerges. For all population groups and both outcome scales, coefficients for Black individuals arrested for possession were positive, yet 6 out of 10 for White citizens were negative.

Robustness

To evaluate the robustness of this analysis I explored whether the model performs well by comparing predicted and actual arrests, and whether changes in law enforcement personnel confound results. For brevity, only population groups showing significant results (2.5k, 10k, and 100k) were analyzed along these lines.

Quantile-quantile plots in Supplemental Appendix A report alignment between model-predicted and actual possession arrests for the population groups of interest in all three arrest categories. These were constructed using Stata's built-in "predict" command and comparing to observed UCR values. As can be seen in the plots, the model performed well, though not so well as to be suspect.

Supplemental Appendix A also contains event studies estimating the relationship between ADCs and law enforcement personnel categorized as total, officers (with arresting power), civilians (no arresting power), and the ratio of officers to civilians.[3] In the 2.5k population group, ADCs were associated with fewer personnel in all three outcomes at or just before implementation. The 10k group showed no effects for personnel numbers but a tendency toward lower officer-to-civilian ratios prior to implementation. Estimates for the 100k group indicated a small association with fewer civilians 4 years prior to implementation, and a higher ratio in the same relative time bin. All significant coefficients come in less than 10%, save that for lower civilians in the 2.5k category. Given their small effect sizes and the inclusion of officers and civilians in the main specification, law enforcement personnel do not likely confound results.

Counterfactual Analysis

To get a clearer picture of how these relationships play out in total number of possession arrests I estimated the total number of crimes predicted by the primary model and the hypothetical situation in which ADCs had not been implemented within this sample using equation (4) from the Supplemental Appendix B and then converting rates per 1,000 population back to total counts. This supplemental method provides an objective perspective on arrest counts that incorporates dynamic estimated effects over time. Figure 5 reports the differences between model predicted and counterfactual arrest counts over time. In all cases, change in arrests of Black residents came in higher than White.

[3] Covariates for officers and civilians per 1,000 covered population were excluded from this analysis.

Table 4 sums predicted-counterfactual differences for the entire study period. These results mirror the annual rates above, with all population groups showing more Black arrests and fewer White.

Limitations

Despite pains to address potential omitted variable bias, and other issues associated with evaluation at this unit-of-analysis (communities, rather than individuals), we cannot make causal inference. Further, processing UCR data involves a tradeoff between data quality and generalizability. By limiting data to agencies covering a certain population figure and report consistently, information is limited to communities within this profile—missing those that do not. It is not likely inclusion criteria variables are distributed randomly, so estimates are not generalizable. Similarly, communities implementing ADCs likely have other capacities (e.g., service provision, criminal justice reform efforts) and social constructions of issues like crime and substance use, which would likely confound analysis. Further work is necessary to make causal inference.

Discussion

The current analysis showed a relationship between communities implementing adult drug treatment courts and drug possession arrests for agencies in the 2.5k, 10k, and 100k population groups. We must tackle some fundamental questions before moving on to interpretation. First, whether to associate ADCs themselves with this variation. As discussed in the limitations section, these programs likely align with other community features like local views on issues of crime and drug use, political appetite for criminal justice reform and service provision, and resources available to implement new programs. ADCs may simply be serving as a proxy variable for some mix of these other factors. More work is needed to make causal inference.

Next, taking results at face value, for argument's sake, the question arises from whence relative changes in possession arrests came. Considering Figure 1 above, these may represent actual drug possessions or changes in law enforcement behavior. The possibility exists of *more* actual drug possessions. Previous work has argued that the balance between lower recidivism rates for those who graduate and benefit from ADCs and higher rates for those who do not may tip toward the latter, possibly resulting in more crime in the community (Belenko, 1999; DeMatteo et al., 2009; Lilley, 2013).

On the other hand, variation in possessions arrests relative to ADC implementation may result from changes in law enforcement behavior. Though this notion has yet to be empirically demonstrated, recent publications aptly argued police may use their discretion in arresting people for low-level offenses in the presence of a program like ADCs (Lilley, 2017; Lilley et al., 2019, 2020). The larger effect sizes for arrests scaled per 1,000 officers, relative to those per 1,000 population, point toward officer discretion as the more likely channel. The opposite coefficient signs between population groups, however, complicates matters.

We can consider two opposing ADC-internal forces, between those that might re-offend less and more, and the external influence of police behavior. If we take these proposed mechanisms universally, that changes in actual possessions and use of discretion apply to both population groups, then we must consider them together: net changes resulting from the balance between internal factors, along with increases in discretionary arrests by police. For rural groups, this would mean not only do possession reductions associated with graduates outweigh increases from non-graduates, but also countervail any increases associated with police discretion. In the 100k group, if we assume a net decrease between graduates and non-graduates, changes in law enforcement behavior negate these *and* create increases community-wide. If we assume a net increase internally, these and, possibly, higher rates of discretionary arrests comprise the estimated increases.

It seems more likely, though, that these mechanisms work differently between population groups, especially if we consider that UCR data do not differentiate between new and repeat offenses. It would be helpful to determine how many of the increased drug possession arrests were associated with previous ADC involvement, how many were first-time arrests, and how closely linked law enforcement actors and ADCs were previous to observation periods (something like a gravity equation model used for international trade; see Chaney, 2013).

For now, we can look to variation in results between outcomes scaled differently between population groups. Referring to Table 3, the 2.5k and 10k population groups indicate smaller increases in arrests of minorities for outcomes scaled to police officers, relative to per 1,000 population, but larger decreases for White and total individuals. The 100k group, on the other hand, indicates more arrests per 1,000 officers in all outcomes, even switching sign from negative to positive for arrests of White individuals (though not statistically significant). From the current evidence, it appears changes in law enforcement behavior influence arrests in more populous regions but not as much in their rural counterparts.

Underneath the notion of police changing their behavior is the assumption that these officers were *aware* of a new ADC. The results here may seem counterintuitive: that this behavior change appears to occur in more populous areas but not rural. Officers working in urban centers confront a more complex environment—more densely populated areas generally feature more programs like ADCs, and services generally (Allard, 2004). It makes sense that police covering urban areas would be less likely to know about an individual program like a drug court. ADC capacity, however, generally scales relative to local population density (Bouffard & Smith, 2005; Collaborative Justice Court Roster, 2020). These specialty court programs diffused across the country rapidly, on a wave of positive press and substantial government funding, and during a time when crime was a salient public issue (Noia et al., 2018). Many people, likely including law enforcement, were aware of ADC implementations. Further, the new programs operated inside the criminal legal system and included actors familiar and institutionally proximate to law enforcement (e.g., district attorney and probation offices), if not representatives from law enforcement specifically (NADCP, 2018a, 2018b; Rossman, Roman, Zweig, Rempel, Lindquist, Willison, et al., 2011). While we cannot determine whether urban police departments were *more* aware of ADC implementation than rural, it is likely they were at least *as* aware. Previous research implicitly demonstrated general law enforcement awareness by exploring their perceptions about ADCs (Gross, 2010).

Though more work is needed to make a causal connection between ADCs and law enforcement behavior, we can consider a few potential reasons why this might be the case and indicate future areas of investigation. Lilley (2017, p. 676, citing Gross, 2010; Hoffman, 2000) offered a compelling argument that officers might feel a “noble cause” to use discretion in arresting individuals, that they perceived the new ADCs as addressing “problems that had previously been overlooked by an overburdened justice system.” So, police may believe themselves part of the new process and that using their discretion to increase possession arrests helps those they arrest, improving community public safety. Lilley et al. (2020, p. 289) expanded this line of reasoning to include “net widening,” in which ADC officials “directly encouraged law enforcement officers to intensify their focus on drug offenses.” More work is needed, though, to fully explore this causal channel, should the literature prove a causal connection between ADCs and community arrests. A study that involves surveys of officers may provide the needed evidence, especially if constructed using a survey experiment design (Sniderman, 2011).

It is also possible that other concurrent efforts may prove responsible for the observed increase in possession arrests in urban areas. The War on Drugs era involved many such efforts, including increased enforcement of laws like those for drug possession. The validity check estimating the relationship between numbers of law enforcement personnel and ADCs (discussed above) detracts from this argument but does not put it to rest, as ADC implementations generally run parallel to an overall concentration on drug crime. A study controlling for other law enforcement efforts would help in settling this issue, though the most robust strategy would be a more precise identification of ADC treatment effects on possessions (e.g., instrumental variable specification).

Disparate results between urban and rural communities may also be a relic of policing approaches like Broken Windows Theory (Harcourt & Ludwig, 2007). This theory posits enforcement of low-level crimes would prevent more serious offenses and became popular through the 1990s and 2000s. More densely populated jurisdictions implemented ADCs earlier than rural areas, aligning well with the Broken Windows phenomenon. Estimated differences in arrests presented in Figure 5 appear to reflect this alignment. The 2.5k and 10k groups indicate changes that begin small and gradually increase over time. The 100k group, on the other hand, shows a rapid increase early that decelerates and declines as years progress. More work is needed to parse out how much of the increase in possession arrests may be attributed to enforcement policies, as opposed to ADCs.

Theoretical Implications

Two themes arise from this analysis: inequitable treatment and urban-rural heterogeneity. In all population groups, Black citizens were disproportionately affected. The only correlations showing statistically significant for the 2.5k and 10k groups were reductions for arrests of White residents, which drove the total arrests outcome as well. With 100k, increased arrests of Black individuals were the driving factor, especially for outcomes scaled to officers.

While the case for disproportionate treatment of minorities by law enforcement has been well documented (e.g., Meehan & Ponder, 2002), several other factors could play into these results. As previous work notes, inequitable access to ADCs, and the benefits thereof, tends to hinge more on life circumstance (e.g., employment, education; Lilley et al., 2019; see also Phillips & Land, 2012) than race specifically. Thus, other structural equity issues may come into play, possibly interacting, even perhaps compounding, inequities. For instance, increases in discretionary arrests may occur in sections of urban areas already over-policed (Brunson & Miller, 2006). A study using a model that interacts ADC indicator variables with those of neighborhoods known to be disproportionately policed may help clarify this question.

The difference between urban and rural communities indicates a direction for future research as well. Overall, it appears police in densely populated jurisdictions may change their behavior, relative to ADC implementation, more readily than their rural counterparts. More work is needed to determine how institutional relationships differ between these community types. Keeping in mind rural areas saw lower arrest rates and urban higher, exploring structural differences between these types of communities may also point toward pathways through which ADC participant outcomes translate to communities.

The question also occurs of whether individuals and communities benefit from increases in possession arrests. Previous work explored this line of inquiry, proposing that community benefits may manifest if those arrested “were, in fact, chemically dependent,” and in need of treatment (Lilley et al., 2019, p. 367). Authors also position the benefits of ADC graduation (e.g., removal of a conviction from defendants’ records) against the burden of participation, which requires onerous time and monetary commitments. Those with resources available to successfully participate may benefit from the program and move on to a life less likely to involve crime. Those without such resources, however, might get caught up in a cycle of incarceration, creating more harm for those arrested and their communities.

The current study cannot determine if communities benefit from this increase, though such determination might be estimated looking at other outcomes relative to increases in possession arrests. If the point of efforts like ADCs and officers arresting individuals for drug possession is to improve public safety, then we should see lower rates of incarceration over time (in both local jails and state prisons) and more serious crimes, as well as public health outcomes like drug overdose deaths and hospitalizations, relative to the increases in possession arrests associated with ADCs. An estimation strategy involving mediator and moderator analysis would prove useful in this instance.

Policy Implications

These results indicate communities would benefit from exploring local relationships between criminal legal system actors. ADCs cultivate relationships within this system, as well as across institutional boundaries (e.g., SUD service providers; NADCP, 2018a). Communities would likely benefit by constructing similar collaborative networks to share information and efforts. For instance, a committee consisting of individuals from ADCs, law enforcement, service providers, and advocacy groups can explore the impact each of their efforts have on community issues like public safety and health, and how these efforts might be coordinated toward more efficient and equitable outcomes.

The glaring inequity displayed in this analysis proves disturbing. It appears the presence of a program like ADCs may magnify existing structural inequities. Thus, work is called for that explores how these relationships might be improved, toward more just treatment of minorities, especially in urban communities. The abovementioned collaborative committee would be a good first step toward addressing this problem, particularly if it includes community partners who can represent those most impacted (i.e., arrested) by the phenomenon.

Conclusion

This study explored the relationship between adult drug treatment courts and drug possession arrests. Results indicate a reduction in arrests of White and total residents associated with ADCs in rural areas (2,500–24,999 population) and increases for all groups in communities with 100,000 or more population, with higher estimates returned for arrests of Black citizens. These results may indicate changes in actual drug possessions in the community or changes in law enforcement behavior, that they increase enforcement of discretionary crimes (such as drug possession) following implementation of a program like ADCs. Comparing estimates between outcomes scaled per 1,000 law enforcement officers with per 1,000 population, the former returned higher coefficients in the 100k group and mixed results for rural groups. These results point toward the reductions seen in less populous communities as likely associated with changes in actual possessions but increases in urban areas with police changing their behavior.

These results highlight inequitable treatment of Black citizens by law enforcement and variation in how these criminal legal system elements (i.e., courts and law enforcement) interact between urban and rural communities. Though more work is needed toward causal inference and exploration of causal mechanisms, communities would benefit from exploring institutional relationships and whether these lead to desired outcomes like equitable treatment and improved public safety.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

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Biography

Patrick Hibbard is a Postdoctoral Research Fellow at OSLC, working with the JEAP Initiative. He studies programs and organizational management in the criminal justice and substance use disorder policy areas, using a variety of methodologies. He is interested in researching and improving programs in these areas, as he identifies as a person with lived experience in both the US criminal justice system and recovery from substance use disorder.

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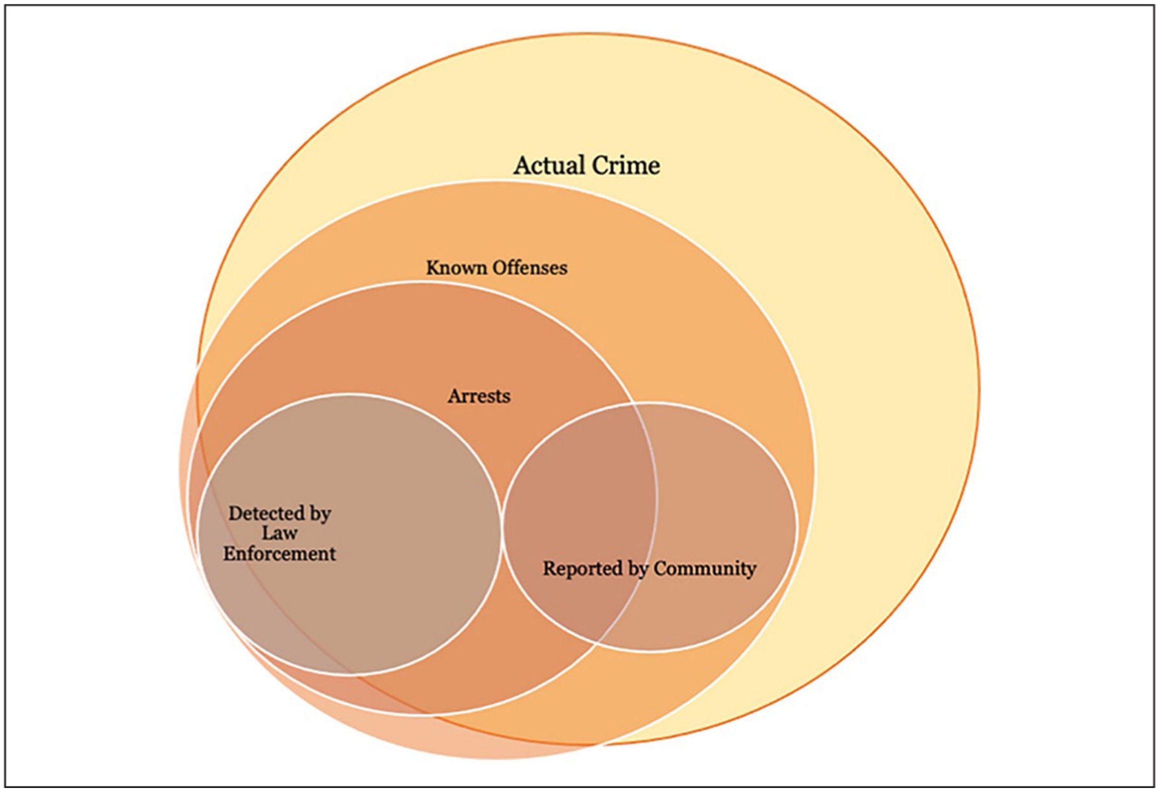

Figure 1.
Types of crime data.

Figure 2.
Drug arrest trends.

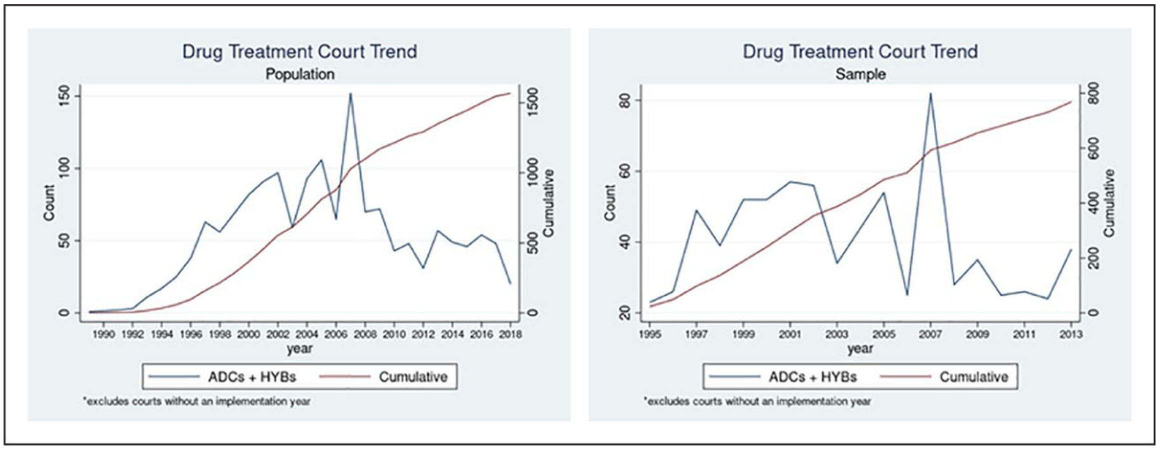

Figure 3.
Drug court implementation trends.

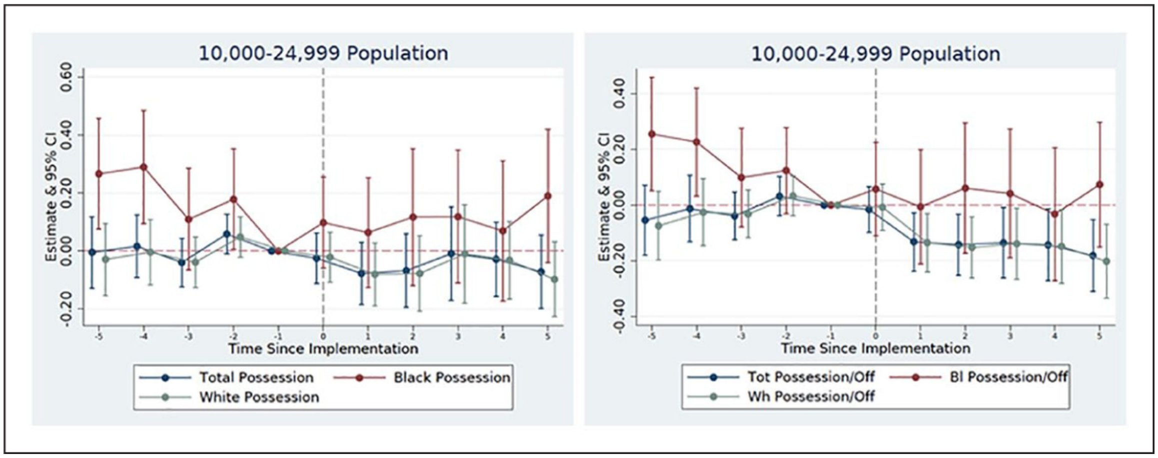

Figure 4.

Ten thousand group event study graphs.

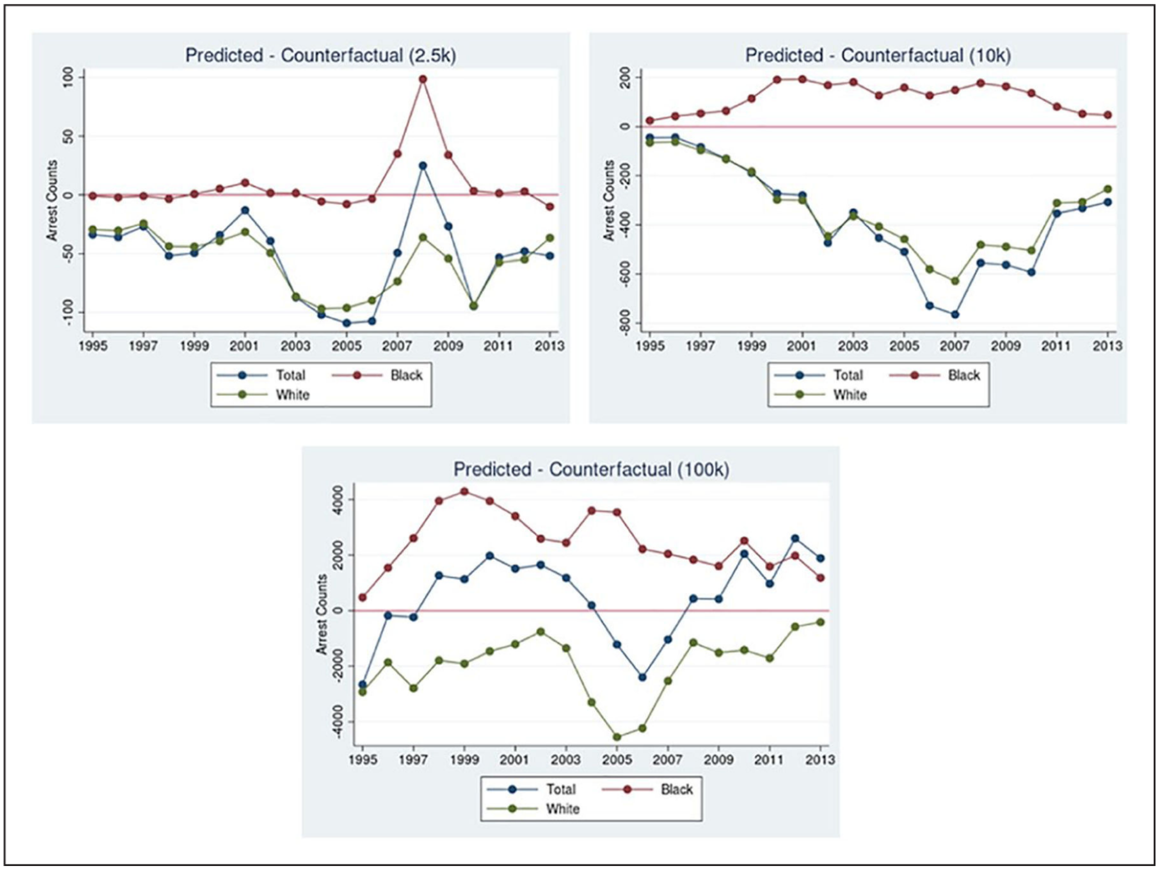

Figure 5.
Crime difference per year.

Table 1.

Summary Statistics.

Variable	Total sample Mean	*SD*	Ever ADC Mean	*SD*	Never ADC Mean	*SD*	*p*-Value	*SD*
Law enforcement personnel (per 1k)								
Total	2.991	2.897	3.015	2.828	2.985	2.912	.437	0.007
Officers	2.104	1.673	2.195	2.230	2.084	1.523	.000	0.041
Civilians	0.923	2.002	0.847	0.880	0.940	2.172	.000	−0.040
Possessions (per 1,000 population)								
Total	4.131	4.684	4.641	5.199	4.019	4.556	.000	0.090
Black	0.867	1.673	0.866	1.443	0.867	1.719	.964	0.000
White	3.205	3.905	3.701	4.609	3.096	3.724	.000	0.102
Possessions (per 1,000 officers)								
Total	2,297	3,823	2,472	2,596	2,259	4,044	.000	0.044
Black	408	773	390	554	412	813	.031	−0.022
White	1,858	3,428	2,038	2,379	1,818.121	3,617	.000	0.051
Socio-economic								
Population	88,071	263,272	170,817	494,292	69,925	170,614	.000	0.193
Pop Density	197.614	690.199	257.925	764.892	184.389	672.001	.000	0.072
% Age 15–24	13.815	3.768	14.376	3.954	13.691	3.714	.000	0.126
% Male	49.546	1.745	49.487	1.481	49.559	1.798	.001	−0.031
% Black	8.756	12.573	7.841	10.761	8.957	12.928	.000	−0.066
% White	88.029	13.355	87.646	11.966	88.113	13.640	.007	−0.026
Unemployment	6.107	2.750	6.024	2.583	6.126	2.785	.004	−0.027
% Rep. pres. votes	53.785	13.793	53.407	12.795	53.867	14.001	.010	−0.024
% Dem. pres. votes	41.344	12.568	42.623	11.870	41.063	12.699	.000	0.090

Table 2.

Court Counts.

	ADC	HYB	Both
Population	1,290	413	1,703
Sample	707	278	985

Table 3.

Dynamic Model Results (1–5 Bin Averages).

	Population group				
Arrest category	**2,500 to 9,999**	**10,000 to 24,999**	**25,000 to 49,999**	**50,000 to 99,999**	**100,000+**
Possession	−0.134 (0.159)	−0.051 (0.060)	−0.003 (0.041)	0.054 (0.050)	0.025 (0.042)
% Change	−12.54%	−4.97%	−0.30%	5.55%	2.53%
Poss Black	0.297 (0.307)	0.112 (0.101)	0.053 (0.076)	0.014 (0.088)	**0.097**+ (0.053)
% Change	34.58%	11.85%	5.44%	1.41%	**10.19%**
Poss White	−0.183 (0.157)	−0.059 (0.062)	0.000 (0.042)	0.062 (0.048)	−0.007 (0.042)
% Change	−16.72%	−5.73%	0.00%	6.40%	−0.70%
Poss/Off	−0.244 (0.152)	**−0.147**** (0.055)	−0.039 (0.041)	0.066 (0.049)	**0.064*** (0.031)
% Change	−21.65%	**−13.67%**	−3.82%	6.82%	**6.61%**
Poss Bl/Off	0.189 (0.297)	0.028 (0.102)	0.041 (0.065)	0.016 (0.083)	**0.109*** (0.046)
% Change	20.80%	2.84%	4.19%	1.61%	**11.52%**
Poss Wh/Off	**−0.289**+ (0.151)	**−0.155**** (0.056)	−0.043 (0.043)	0.073 (0.051)	0.045 (0.032)
% Change	**−25.10%**	**−14.36%**	−4.21%	7.57%	4.60%

Note. Standard errors in parentheses.

Bolded text indicates significant findings.

+ $p < .10$.

* $p < .05$.

** $p < .01$.

*** $p < .001$.

Table 4.

Total Predicted-Counterfactual Differences.

Pop group	Total predicted	Total CF	Total Diff	Total perc diff
2.5k	61,611	62,599	−989	−1.60%
10k	531,108	538,132	−7,024	−1.32%
100k	7,258,788	7,249,219	9,569	0.13%
	Black predicted	Black CF	Black diff	Black perc diff
2.5k	6,833	6,672	161	2.36%
10k	86,085	83,833	2,252	2.62%
100k	2,493,247	2,445,829	47,419	1.90%
	White Predicted	White CF	White diff	White perc diff
2.5k	52,834	53,902	−1,068	−2.02%
10k	435,232	441,597	−6,365	−1.46%
100k	4,684,628	4,722,095	−37,467	−0.80%