Education, Income, Racial Composition, and Urbanization: An Examination of Factors that Affect Intervention Court Participation and Drug-Related Arrests in Mississippi

Will Hengehold

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Education, Income, Racial Composition, and Urbanization: An Examination of Factors that Affect Intervention Court Participation and Drug-Related Arrests in Mississippi

by
Will Hengehold

A thesis submitted to the faculty of The University of Mississippi in partial fulfillment of the requirements of the Sally McDonnell Barksdale Honors College

Oxford
April 2022

Approved by

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# List of Abbreviations Used in This Paper

<table>
<thead>
<tr>
<th>Abbreviation</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>AMHI</td>
<td>average of median household incomes</td>
</tr>
<tr>
<td>Delay</td>
<td>delay of intervention court adoption</td>
</tr>
<tr>
<td>DRA</td>
<td>drug-related arrests</td>
</tr>
<tr>
<td>DRAPC</td>
<td>drug-related arrests per capita</td>
</tr>
<tr>
<td>DTC</td>
<td>drug treatment court</td>
</tr>
<tr>
<td>FE</td>
<td>fixed-effects</td>
</tr>
<tr>
<td>ICE</td>
<td>intervention court exits</td>
</tr>
<tr>
<td>ICPEC</td>
<td>intervention court exits per capita</td>
</tr>
<tr>
<td>LDV</td>
<td>lagged-dependent variable</td>
</tr>
<tr>
<td>MHI</td>
<td>median household income</td>
</tr>
<tr>
<td>NCP</td>
<td>new intervention court participants</td>
</tr>
<tr>
<td>NCPPC</td>
<td>new intervention court participants per capita</td>
</tr>
<tr>
<td>NCPperDRA</td>
<td>new intervention court participants as a percentage of drug-related arrests</td>
</tr>
<tr>
<td>NHW</td>
<td>percentage of residents who identify as non-Hispanic Whites</td>
</tr>
<tr>
<td>OLS</td>
<td>ordinary least squares</td>
</tr>
<tr>
<td>SC</td>
<td>successful intervention court completions</td>
</tr>
<tr>
<td>SCPC</td>
<td>successful intervention court completions per capita</td>
</tr>
<tr>
<td>SCperICE</td>
<td>successful intervention court completions as a percentage of total exits</td>
</tr>
<tr>
<td>URB</td>
<td>percent of residents who live in urban areas</td>
</tr>
</tbody>
</table>
ABSTRACT

WILL HENGEHOLD: EDUCATION, INCOME, RACIAL COMPOSITION, AND URBANIZATION: AN EXAMINATION OF FACTORS THAT AFFECT INTERVENTION COURT PARTICIPATION AND DRUG-RELATED ARRESTS IN MISSISSIPPI
(Under the direction of Dr. John Conlon)

This paper serves as an evaluation of Mississippi Intervention Courts and attempts to determine the effectiveness and use of those courts. The regressions in this paper attempt to show how the use of intervention courts and demographic characteristics of Mississippi District Circuit Courts affect the number of drug-related arrests in Mississippi, how the number of drug-related arrests and demographic characteristics of Mississippi district circuit courts areas affect intervention court use and intervention court participation rates in Mississippi, and how demographic characteristics affected the delay in the adoption of intervention courts by Mississippi District Circuit Courts. Demographic characteristic variables used include education, income, racial composition, and urbanization. Regression analyses including ordinary least squares regressions, lagged-dependent variable regressions, and fixed-effects models are used in this paper to determine these effects. Many of the coefficients on the variables in these regressions are statistically insignificant. However, the regression of intervention court use on drug-related arrests per capita and demographic characteristics does conclude that an increase in the number of drug-related arrests per capita decreases the use of intervention courts in Mississippi by a substantial amount. The results from these regressions, along with input from Judge Starrett, the founder of the first intervention court in Mississippi, are used to justify a recommendation to Mississippi legislators to increase intervention court use in times of rising drug-related arrests.
Chapter 1: An Introduction to Intervention Courts

An Overview of Intervention Courts

The “War on Drugs” was a major event in the history of drug use in the United States. Nixon’s policies on drug crime decreased the supply of illegal drugs entering the United States and the number of drugs being used by Americans substantially; however, the cost of those policies was not solely increased budgets for federal drug-control agencies. At this time, the average cost to imprison someone for a year was over $30,000 (Kyckelhahn, 2014), and Nixon introduced measures such as mandatory sentencing and no-knock warrants to put his enemies in the war behind bars more easily. From 1980 to 1997, the number of people behind bars for non-violent drug offenses, therefore, increased from 50,000 to over 400,000 (Drug Policy Alliance, 2020). Thus, people began to see the need to combat the rising cost of incarcerating drug offenders. In 1989, the first Felony Drug Treatment Court (DTC) was founded in Dade County, Florida on the premise that addiction is more of a disease than a crime (Lurigio, 2008). This court system would serve as a template for many other DTCs to come over the next few decades.

It was not long until the state of Mississippi followed suit. The Hon. Judge Keith Starrett created the first DTC in Mississippi in 1999 in the 14th Judicial Circuit Court District. “We started the drug court in 1999, when we were at the height of the crack explosion… Crack is a tough drug to get people off of” (Judge Starrett, personal communication). This was a time when many drug addicts and drug abusers would have benefited from the existence of an alternative to incarceration; an alternative providing a much more robust support network and better access to rehabilitation services. To create this path for criminal drug addicts and drug abusers, Judge Starrett first had to get support from the state legislature. Here’s what he had to say about starting the first DTC in Mississippi: “I needed good numbers to get the legislature to pay attention and to look at this program as a viable alternative (to incarceration). So, we put a lot of people in there that we figured could succeed, and they did, and we got some good statistics. The legislature paid attention and the program started being developed.” Shortly after Judge Starrett gained approval from state legislators, the concept caught on and, in 2003, a law was passed allowing for the creation of Felony Intervention Courts statewide at chancery, circuit, county, youth, municipal, or justice court levels (State of Mississippi Judiciary, no date). But, in retrospect, Judge Starrett said that picking the “low-hanging fruit”, those low-risk offenders whom you know will probably succeed even without DTCs, was not the best way to do it: “you go after the high-risk offenders. That’s who you want because you’re spending a lot of money on the program. Why waste resources on people who don’t need it?”

Shortly after the law was passed, at the legislative session in Jackson, State Auditor Phil Bryant released the results of a feasibility study conducted by the performance audit division of his office, calling the Intervention Court system an “effective, community-based strategy to reduce
drug use and crime, generate cost savings at the local and state level and allow statewide exchange of information between Circuit Court districts”. The report went on to estimate a cost-savings of 5.4 million dollars per year for every 500 participants in Mississippi Intervention Courts (State of Mississippi Judiciary, no date). After serving as a DTC judge in Mississippi for 6 years, Judge Starrett went on to serve as the chairman of the National Association of Drug Court Professionals (NADCP) where he helped spread the use of DTCs in areas across the nation. Today, intervention courts around the nation are on average very effective in keeping participants drug-free. As Judge Starrett put it, “after three years, 75% of the people who completed the (DTC) program were still drug-free. That’s a national statistic that was verified by our experience in the fourteenth district. Before drug courts, 25% would be clean and sober after three years” (Judge Starrett, personal communication). The developments made by Judge Starrett and other proponents of DTC programs laid the groundwork for an efficient system that keeps up the fight against drugs by treating non-violent drug abusers rather than punishing them. Additionally, these programs save the state substantial amounts of funds that otherwise would be spent on imprisoning these offenders.

Today, there are 22 Intervention Courts in Mississippi; one in each of the 22 circuit court districts. Each of these courts must incorporate 10 key components of drug courts into their program, outlined by the Bureau of Justice Assistance of the U.S. Justice Department. These key components include:

1. Drug courts integrate alcohol and other drug treatment services with justice system case processing.
2. Using a non-adversarial approach, prosecution and defense counsel promote public safety while protecting participants’ due process rights.
3. Eligible participants are identified early and promptly placed in the drug court program.
4. Drug courts provide access to a continuum of alcohol, drug, and other related treatment and rehabilitation services.
5. Abstinence is monitored by frequent alcohol and other drug testing.
6. A coordinated strategy governs drug court responses to participants’ compliance.
7. Ongoing judicial interaction with each drug court participant is essential.
8. Monitoring and evaluation measure the achievement of program goals and gauge effectiveness.
9. Continuing interdisciplinary education promotes effective drug court planning, implementation, and operations.
10. Forging partnerships among drug courts, public agencies, and community-based organizations generates local support and enhances drug court program effectiveness.

(Bureau of Justice Assistance, 1999)
These components of intervention courts are not the only determinants of success for program participants. In my interview with Judge Starrett, he told me that a supportive family and well-trained DTC professionals, such as court officers and coordinators, can help keep participants on track with their progress in the program. Additionally, job programs help fill the participant’s time with positive rather than negative surroundings and socialization programs help to surround the participants with positive role models (Judge Starrett, personal communication). These additional key components are as important as the 10 key components outlined above. If all of these components of DTCs are satisfied, the program can provide life-changing assistance to those addicted to drugs or abusing drugs, save the state money that would have been spent on incarceration, and reduce the number of drug-related crimes in an area.

Purpose and Significance of This Research

One of the key components of drug courts (component 8) requires that drug courts monitor and evaluate the achievement of program goals and gauge effectiveness. My paper serves as an attempted evaluation of Mississippi Intervention Courts and uses statistical methods to determine the effectiveness of Mississippi Intervention Courts in reducing drug-related arrests. Since my data is limited, and since intervention court programs in Mississippi are still relatively small compared to the number of drug-related arrests, I have difficulty measuring any effects of intervention courts on aggregate drug crime.

Later on, in this paper, I therefore turn to an attempt to determine when intervention courts are more likely to be used, and when they are more likely to be successful in terms of successful completions of the program. In particular, I look at the effect of the number of drug-related arrests per capita and demographic variables on intervention court participation and intervention court success rates. Finally, I look at how demographic variables affected the delay in the adoption of intervention courts by district circuit courts. The initial regressions presented in this paper try to identify causal relationships within the regressions described above. However, only three years of data are currently available for my initial set of regressions, and only one year of data is available for the subsequent regressions. Therefore, it is difficult to learn much from the data.

Hopefully, this paper can therefore be expanded upon when additional data becomes available for subsequent years. Also, additional variables could be added to assess Mississippi Intervention Courts’ abilities to reduce recidivism for felony drug offenders, reduce overdose deaths, and discourage violent crimes among drug abusers and drug addicts.
Chapter 2: Review of Prior Literature

Since the first DTC was adopted in 1989, there have been many studies gauging the effectiveness of the programs. Quite a few of those studies try to assess the effectiveness of DTCs across the country by using drug crime recidivism as the main metric. One such study (Kearley and Gottfredson, 2019) compares variables such as the amount of time spent in incarceration and the rate of recidivism from a random sample of drug court participants from the Baltimore City DTC to a control group of drug offenders who received traditional adjudication. In authors' conclude that offenders who participated in the Baltimore City DTC had lower mortality rates, fewer days of incarceration, and lower cumulative rates of recidivism (including both arrests and convictions) after 15 years, as compared to the control group (Kearley and Gottfredson, 2019).

Another study that measures DTC effectiveness using recidivism (Rampel et al., 2012) uses three variables to compare offenders from 23 DTC programs to offenders from six comparison groups. The three variables studied are self-reported criminal behavior up to 18 months after release, official re-arrests up to 24 months after release, and the sentence length on the case that brought the offenders to either the intervention court or a comparison court in the first place, referred to as the “precipitating case”. This is the only study I have found that records study participants’ self-reported criminal behavior. It is likely that not all participants who committed criminal acts after DTC graduation or release from a comparison program reported those acts. However, the ability of this study to capture some of the criminal acts that go unnoticed by law enforcement provides a more accurate measure of the number of crimes that are committed by the study participants than just official re-arrests alone. In the conclusion, the authors find that DTCs reduce criminal acts by more than 50% over 18 months but do not reduce the average sentence length on the precipitating case. Even though DTC participants who graduate from the program receive very little or no time in prison, those who fail the program usually receive an increased sentence over what they would have been given had they not entered the program at all (Rampel et al., 2012).

The two aforementioned studies mainly look at how the use of DTCs affect recidivism rates for its participants. However, it is not possible for me to look at recidivism rates in Mississippi, given that I do not have access to program participants to interview or documents that record such measures. Additionally, these studies look at the overall effectiveness of DTC programs across the country, while I specifically want to narrow the scope of my research to just the state of Mississippi.

Currently, the only evaluation of Mississippi DTCs listed on the Intervention Courts page of the State of Mississippi Judiciary website is a paper prepared by the Mississippi Department of Statistical Analysis (Nored et al., 2007), which looks at demographic characteristics within six Mississippi Intervention Courts jurisdictions including race, gender, type of offense, and whether
the offender graduated from the intervention court. This study aimed to identify whether or not intervention court judges, participants, and court officers were satisfied with the effectiveness of the courts. The authors concluded that there is an absence of standardized data-collection procedures between courts, and recommended that the courts implement a state-wide management information system (MIS) to facilitate data management. The paper also recommends that the courts increase intervention court personnel and acquire increased state and local funding to increase the number of participants the courts can accommodate, to reduce the number of drug offenders incarcerated in state and local prisons (Nored et al., 2007).

In my research, I have not been able to find a study that looks at the effect of intervention courts on drug-related arrests in Mississippi, so I hope to shed light on this issue. Another topic missing from the current literature concerns when intervention courts are actually used by the judicial system. This paper therefore also looks at the effect of the number of drug-related arrests and demographic characteristics on the intervention court participation rate and the intervention court completion rate. I also look at the effect that certain demographic characteristics have on the delay in intervention court adoption by district circuit courts. I hope to quantify these effects in this paper so that the state legislature can use my results to possibly guide their decision-making processes to improve Mississippi Intervention Courts.

Chapter 3: Methodology

To conduct a statistical analysis on the efficacy of Mississippi Intervention Courts, I first needed to identify a few variables on which I would need to collect data. The dependent variable I use in the initial analyses is the number of drug-related arrests per capita by circuit court district. Given that I could not find data on drug use by circuit court district and I do not have access to data on individual intervention court participants, the number of drug-related arrests per capita is the best dependent variable I can use to quantify how well these courts reduce drug use. The independent variable I use in the initial analysis is the number of successful intervention court completions by circuit court district per capita, which quantifies the number of drug-related offenders who benefit from the program being in place as a percentage of the total district circuit court population. For each of these variables, I decided to collect a cross-sectional time-series data set so I could look at the effect of intervention court completion on drug use between different courts in Mississippi as well as between the different years that intervention courts have been used.

Data Collection

The initial plan for the analyses was to collect data on all of the variables included in this analysis for each district circuit court over the four years before each Mississippi Intervention
Court was created as well as the four years after each Mississippi Intervention Court was created. I wanted to be able to perform a difference-of-differences analysis that looks at how the creation of intervention courts affected drug-related arrests. However, the Mississippi Supreme Court has just recently started to release quantitative data on drug courts through their annual reports. I was able to find the number of successful drug court completions for 2020 by circuit court district in the 2020 Annual Report, and, after corresponding with the court’s Public Information Officer, Beverly Kraft, I was able to obtain the number of successful drug court completions for 2018 and 2019 by circuit court district as well. It was not possible to find the number of successful intervention court completions for the four years before intervention court was created in Mississippi, as many of the district intervention courts were established between 2001 and 2011, and quantitative data on their successes have not been recorded until 2018, as far as I know.

The Mississippi Prescription Monitoring Program’s website provides data on the number of drug-related arrests by county in Mississippi for the years 2017 to 2020. To make this data consistent with the data on successful drug-court completions, I had to determine the number of drug-related arrests for each district by adding the number of drug-related arrests in each county in that district.

To control for the fact that some districts have higher populations, and are therefore more likely to have a higher number of drug-related arrests (DRA) and successful Intervention Court completions (SC), DRA and SC were transformed into per capita measures by dividing each data point by the total population in the corresponding district and year, resulting in drug-related arrests per capita (DRAPC) and successful intervention court completions per capita (SCPC).

After a preliminary analysis of the effect of the number of successful intervention court participants per capita on the number of drug-related arrests per capita using an OLS regression with no controls and robust standard errors, I saw an unexpected positive, but insignificant, relationship between these variables (Figure 3.1). All regressions in this paper were performed using Gretl software for Mac OS.
**Figure 3.1: OLS Regression of DRAPC on SCPC**

Model 1: Pooled OLS, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: DRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>0.463749</td>
<td>0.0944569</td>
<td>4.910</td>
<td>7.42e-05 ***</td>
</tr>
<tr>
<td>SCPC</td>
<td>1.17091</td>
<td>3.51040</td>
<td>0.3336</td>
<td>0.7420</td>
</tr>
</tbody>
</table>

Mean dependent var: 0.485200
S.D. dependent var: 0.287936
Sum squared resid: 5.375948
S.E. of regression: 0.289826
R-squared: 0.002418
Adjusted R-squared: -0.013169
F(1, 21): 0.111258
P-value(F): 0.742023
Log-likelihood: -10.89519
Akaike criterion: 25.79038
Schwarz criterion: 30.16969
Hannan-Quinn: 27.52085
rho: 0.811751
Durbin-Watson: 0.154016

This figure shows the results from an ordinary least squares (OLS) regression of DRAPC on SCPC. DRAPC denotes drug-related arrests per capita and SCPC denotes successful intervention court completions per capita. P-values with three asterisks (***)) indicate that the coefficient on that variable is statistically significant at an alpha level of 0.01. Two asterisks (**) and one asterisk (*) indicate that the coefficient on that variable is statistically significant at alpha levels of 0.05 and 0.1, respectively.

At first glance, this analysis seems to indicate that each additional SCPC increased the number of drug-related arrests in that circuit court district by about 1.17 between the years of 2018 to 2020. This is the opposite of what one would expect, given that each district court has created an intervention court aimed at reducing the number of drug-related arrests in their district. However, upon closer inspection, this positive relation could be the result of reverse causality within the model, meaning that instead of more intervention courts causing an increased number of drug-related arrests, more drug-related arrests precipitate a need for more drug courts.

To try to reduce this problem of reverse causality, more variables were added as controls in an attempt to isolate the causality between the number of drug-related arrests and the number of successful intervention court participants. The median household income (MHI), percent of non-Hispanic White residents (NHW), and the percentage of residents with a high-school diploma (HSD) in each county were recorded from the Federal Reserve’s FRED website. The level of urbanization (URB) was collected for each county from the U.S. Census Bureau for the year 2010. URB is the percentage of the total population in each county that is classified as urban. The 2010 data on urbanization levels is the most recent data available; however, given that urbanization levels do not drastically change over time, I do not think it is too misleading to use these same values for the years 2018-2021. The data on MHI, NHW, HSD, and URB was then weighted by the population of the respective county as a percentage of the total district population and summed to transform the county-level data into population-weighted variables.
for each district, so that the data for the dependent and independent variables were consistent with each other. For example, for the MHI we get the average MHI or AMHI:

$$AMHI_{Di} = \sum_{j=1}^{n_i} \left( \frac{P_{Cj}}{P_{Di}} \right) * MHI_{Cj}.$$ 

Here, $n_i$ represents the number of counties in each circuit court district, $i$, while $j$ indexes counties within the circuit court district, $P_{Cj}$ represents the county-level population, $P_{Di}$ represents the district-level population, $MHI_{Cj}$ represents the median household income in each county, and $AMHI_{Di}$ represents the average of median household income for each district weighted by each county’s median household income in each district. The same equation was used for NHW, HSD, and URB.

### Descriptive Statistics

**Figure 3.2: Initial Summary Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Median</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRAPC</td>
<td>0.48520</td>
<td>0.47086</td>
<td>0.0000</td>
<td>1.1137</td>
<td>0.28794</td>
</tr>
<tr>
<td>SCPC</td>
<td>0.018320</td>
<td>0.016801</td>
<td>0.0000</td>
<td>0.051166</td>
<td>0.0123093</td>
</tr>
<tr>
<td>AMHI</td>
<td>43930</td>
<td>43226</td>
<td>30305</td>
<td>70115</td>
<td>8791.4</td>
</tr>
<tr>
<td>NHW</td>
<td>52.648</td>
<td>56.720</td>
<td>24.950</td>
<td>75.730</td>
<td>15.845</td>
</tr>
<tr>
<td>HSD</td>
<td>82.974</td>
<td>83.260</td>
<td>75.690</td>
<td>90.430</td>
<td>3.8528</td>
</tr>
<tr>
<td>URB</td>
<td>44.555</td>
<td>39.385</td>
<td>5.1700</td>
<td>84.720</td>
<td>19.838</td>
</tr>
</tbody>
</table>

*DRAPC denotes drug-related arrests per capita, SCPC denotes successful intervention court completions per capita, AMHI denotes the average of county-level median household incomes, NHW denotes the percentage of residents who identify as non-Hispanic Whites, HSD denotes the percentage of residents who have obtained a high school diploma, and URB denotes the percentage of residents who live in urbanized areas.*

The above figure (Figure 3.2) presents some simple summary statistics for each of the included variables. AMHI is in dollars, while each other variable is in percentage terms (for example, the mean DRAPC value is 0.4852 %).

Additionally, note that there were a total of 1560 successful intervention court completions in Mississippi from 2018 to 2020, and a total of 50,786 drug-related arrests in Mississippi over the same time-period. This means that the percentage of offenders charged with drug-related offenses who participated in and successfully completed an intervention court program is only about 3.07% of arrests. Therefore, it is not surprising that SCPC had no significant effect on DRAPC in Figure 3.1 above.
**Figure 3.3**

<table>
<thead>
<tr>
<th></th>
<th>DRAPC</th>
<th>SCPC</th>
<th>AMHI</th>
<th>NHW</th>
<th>HSD</th>
<th>URB</th>
</tr>
</thead>
<tbody>
<tr>
<td>DRAPC</td>
<td>1.0000</td>
<td>0.0492</td>
<td>0.6342</td>
<td>0.4752</td>
<td>0.7011</td>
<td>0.2487</td>
</tr>
<tr>
<td>SCPC</td>
<td>1.0000</td>
<td></td>
<td>0.0727</td>
<td>-0.1308</td>
<td>-0.1982</td>
<td></td>
</tr>
<tr>
<td>AMHI</td>
<td>1.0000</td>
<td>0.6299</td>
<td></td>
<td>0.7638</td>
<td></td>
<td>0.2667</td>
</tr>
<tr>
<td>NHW</td>
<td>1.0000</td>
<td>0.5042</td>
<td></td>
<td></td>
<td></td>
<td>-0.2430</td>
</tr>
<tr>
<td>HSD</td>
<td></td>
<td>1.0000</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>URB</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>1.0000</td>
</tr>
</tbody>
</table>

*DRAPC* denotes drug-related arrests per capita, *SCPC* denotes successful intervention court completions per capita, *AMHI* denotes the average of county-level median household incomes, *NHW* denotes the percentage of residents who identify as non-Hispanic Whites, *HSD* denotes the percentage of residents who have obtained a high school diploma, and *URB* denotes the percentage of residents who live in urbanized areas.

The above figure (Figure 3.3) presents a correlation matrix that lists the correlations between each pair of variables on a scale of -1 to 1, where a correlation of -1 means that the two variables are perfectly negatively correlated, a correlation of 0 means the variables are not correlated at all, and a correlation of 1 means the variables are perfectly positively correlated. The largest negative correlation coefficient exists between URB and NHW at -0.2430. This means that in more urbanized areas, a lower percentage of residents are non-Hispanic Whites. The correlation coefficient closest to 0 exists between DRAPC and SCPC at 0.0492, meaning that the number of drug-related arrests per capita in an area is not highly correlated with the number of successful intervention court completions per capita in that area. The largest positive correlation coefficient, other than the correlation coefficient of a variable with itself (e.g. DRAPC on DRAPC) exists between AMHI and HSD at 0.7638. This means that household incomes are higher on average in areas with a higher percentage of residents who have obtained a high school diploma.

It is important to look at the correlation coefficients between DRAPC and AMHI, NHW, HSD, and URB to see how our control variables are correlated with our dependent variables. This will give us an idea of how well our control variables will be able to explain the variation of DRAPC. The correlation coefficient between DRAPC and AMHI is highly positive at 0.6342. This means that a higher number of drug-related arrests per capita is correlated with higher household incomes. One possibility is that higher-income people in Mississippi are more likely to commit drug crimes than low-income people in Mississippi. An alternative reason for this correlation could be because areas with higher household incomes have larger law enforcement budgets, so there are more of all types of arrests, including drug-related arrests.
For the correlation between DRAPC and URB we see a positive value of 0.2487, meaning that there are a higher number of drug-related arrests per capita in urban areas as opposed to rural areas. This is an interesting correlation. I would expect that, with the high concentration of people in urban areas, it would be more difficult for law enforcement to crack down on drug crime. However, it may be that Mississippi police officers in urban areas are more efficient at stopping drug crime than Mississippi police officers in rural areas. Another possible explanation for this correlation could be simply that there are a higher number of drug-related crimes per capita in urban areas than in rural areas, and Mississippi police officers in urban areas are no more efficient at stopping drug crime than Mississippi police officers in rural areas.

The correlation coefficient between DRAPC and NHW is also positive at 0.4752, meaning that a higher number of drug-related arrests per capita is correlated with a higher percentage of non-Hispanic Whites in the population. Because there are a higher number of drug-related arrests per capita in urban areas than rural areas and urban areas have a lower number of non-Hispanic whites than rural areas, there must be something else going on to cause this positive correlation. One possible reason that the correlation between DRAPC and NHW is positive could be that non-Hispanic Whites may be more likely to be arrested for drug crimes in Mississippi than other races. Another possible reason may be that AMHI and NHW are highly positively correlated at 0.6299 and AMHI and DRAPC are also highly correlated, as mentioned above. This may be the reason for the positive correlation, as NHW is much more positively correlated with AMHI than it is negatively correlated with URB.

Lastly, DRAPC is highly positively correlated with HSD at 0.7011. This means that areas with higher drug-related arrests per capita have a higher percentage of residents with a high school diploma, on average. Given that AMHI is highly correlated with DRAPC and HSD, this positive correlation may make sense: areas with higher HSD are likely to have higher household incomes and are therefore more likely to have higher drug-related arrests per capita. Another reason that these variables are highly positively correlated could simply be that those with high school diplomas are more likely to commit drug crimes.

My initial expectation was that high-income, well-educated non-Hispanic Whites should be less likely to be arrested for drug-related crimes. However, higher income, more well-educated areas with more non-Hispanic whites have a larger number of drug-related arrests per capita compared to areas with low income, less educated residents, and more people who identify as Hispanic and/or non-White. My initial expectation could still be accurate though. It may not be that high-income; well-educated non-Hispanic Whites are more likely to be arrested for drug-related crimes. Instead, areas with more of those people might have stricter laws regarding drug use and distribution and are also more urbanized, given that urbanization is highly positively correlated with HSD, positively correlated with AMHI, and negatively correlated only with NHW.
Additional Statistical Methodologies

In addition to adding control variables, there are a few other ways to reduce the level of reverse-causality in this regression. The first is to include a lag of DRAPC into the analysis. Figure 3.4 shows the relationship between DRAPC and DRAPC of the prior year, i.e., DRAPC\textsubscript{t-1}. This relationship is strongly positive, meaning that a high number of drug-related arrests this year most likely leads to a high number of drug-related arrests next year. When we control for lagged drug crime by including DRAPC\textsubscript{t-1} in the regression, the coefficient on SCPC is not forced to pick up the effect of last year’s DRAPC on this year’s DRAPC. Thus, the inclusion of a lag of DRAPC helps reduce omitted variable bias if drug-related arrests last year are correlated with any of the omitted variables.

Figure 3.4

The second method used to reduce the effects of reverse causality in this analysis is the addition of fixed effects. The data were tabulated into a panel data set, and a control dummy variable was created for each circuit court district. A fixed-effects analysis can completely control for cross-sectional omitted variable bias by isolating the effects of only the intertemporal variations in the included independent variables on the dependent variable. However, this only eliminates the omitted variable problem if one can assume that all omitted variables are intertemporally constant, meaning they do not change over time. This is a strong assumption, but it must be made to justify a fixed-effects analysis.
Chapter 4: Effectiveness of Intervention Courts

The following table (Table 4.1) includes a summary of the regression performed in Chapter 3 above (Figure 3.1), along with five additional regressions. The first additional regression introduces control variables into the OLS regression, the second introduces a lag of DRAPC, but with no control variables, the third includes control variables and a lag of DRAPC, the fourth uses a fixed-effects analysis but with no control variables, and the fifth uses a fixed-effects analysis and includes control variables. The $R^2$ value, a measure of how well the included variables account for the variation in the dependent variable, was calculated for each regression, as well as the p-value of the F-statistic, which measures whether the regression as a whole is statistically significant. A regression might contain no statistically significant coefficients but can still have a statistically significant p-value of the F-statistic if the coefficients are jointly significant. It is therefore important to include this measure so that no regressions are thrown out undeservedly.

Additionally, regressions were also performed with variables normalized about their means. For example, the SCPC was normalized about its mean using this equation:

$$Normalized \text{ SCPC} = \frac{(SCPC_i - \overline{SCPC})}{SD(SCPC)}.$$  

Here, $\overline{SCPC}$ represents the mean of all SCPC data points and $SD(SCPC)$ represents the standard deviation of all SCPC data points. The same equation was used for each variable contained in the regressions. Coefficients were normalized about their means in this analysis to more easily compare the effect of one independent variable to the effects of other independent variables on the dependent variable. The top number in each cell of Table 4.1 is the coefficient from the unnormalized regression, the middle number is the coefficient from the normalized regression, and the bottom number is the p-value associated with those coefficients.

The discussion of Table 4.1 is divided into numbered paragraphs, each discussing each separate regression individually to make it easier for the reader to reference the table while reading the discussions. The discussion of Regression 2 begins with (2), the discussion of Regression 3 begins with (3), and so on.
Table 4.1: Summary of Initial Regressions

<table>
<thead>
<tr>
<th>DRAPC on SCPC</th>
<th>Coefficient on SCPC</th>
<th>Coefficient on AMHI</th>
<th>Coefficient on NHW</th>
<th>Coefficient on HSD</th>
<th>Coefficient on URB</th>
<th>R-squared value</th>
<th>Number of Obs.</th>
<th>P-value(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1) OLS with No Controls</td>
<td>1.17 (0.049)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.0024</td>
<td>66</td>
<td>0.742</td>
</tr>
<tr>
<td>(2) OLS with Controls</td>
<td>2.81 (0.118)</td>
<td>5.83E-06 (0.178)</td>
<td>0.0072 (0.0396)</td>
<td>0.0443 (0.0593)</td>
<td>-0.00094 (0.005***)</td>
<td>0.537</td>
<td>66</td>
<td>3.58E-07***</td>
</tr>
<tr>
<td>(3) LDV with No Controls</td>
<td>-0.598 (0.025)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.801</td>
<td>44</td>
<td>2.17E-13***</td>
</tr>
<tr>
<td>(4) LDV with Controls</td>
<td>-1.085 (0.0456)</td>
<td>1.54E-06 (0.047)</td>
<td>0.004 (0.2214)</td>
<td>-0.0123 (0.013**)</td>
<td>-0.0164 (0.2073)</td>
<td>0.000195 (0.0135)</td>
<td>0.845</td>
<td>44</td>
</tr>
<tr>
<td>(5) FE with No Controls</td>
<td>-2.18 (.0916)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.905</td>
<td>66</td>
<td>0.142</td>
</tr>
<tr>
<td>(6) FE with Controls</td>
<td>-1.85 (0.0776)</td>
<td>9.67E-06 (0.295)</td>
<td>-0.042 (0.0135**)</td>
<td>-0.0016 (0.0219)</td>
<td>-</td>
<td>0.916</td>
<td>66</td>
<td>0.0283**</td>
</tr>
</tbody>
</table>

The first column in the above table specifies which regression is being summarized in that row. The number in parentheses before the regression description indicates the regression number. OLS indicates an ordinary least squares regression, LDV indicates a lagged-dependent variable regression, and FE indicates a fixed-effects model. “Controls” refer to demographic control variables. Numbers in columns 2-6 show the coefficient on the variable (the top value), the coefficient for the normalized regression (the middle value), and the p-value associated with that coefficient (the bottom value). The final column in this table shows the p-value of the F-statistic for the regression, denoted as p-value(F). P-values with three asterisks (*** ) indicate that the coefficient on that variable is statistically significant at an alpha level of 0.01. Two asterisks (**) and one asterisk (*) indicate that the coefficient on that variable is statistically significant at alpha levels of 0.05 and 0.1, respectively. DRAPC denotes drug-related arrests per capita, SCPC denotes successful intervention court completions per capita, AMHI denotes the average of county-level median household incomes, NHW denotes the percentage of residents who identify as non-Hispanic Whites, HSD denotes the percentage of residents who have obtained a high school diploma, and URB denotes the percentage of residents who live in urbanized areas.

(1) Regression 1 contains a positive coefficient on SCPC of 1.17, meaning that an increase of 1 percentage point in successful intervention court completions per capita (an increase of about 5 participants on average per year) would increase the number of drug-related arrests per capita by 1.17, or the total number of drug-related arrests by about 280 on average per year. However, this coefficient is statistically insignificant, so it cannot be concluded that successful intervention court completions have any effect on drug-related arrests in Mississippi from this regression. Additionally, given that the $R^2$ value of this regression is so low, the number of successful completions does not explain much of the variation in the number of drug-related arrests.
(2) Regression 2 contains a more positive coefficient on SCPC than Regression 1. This means that even when we control for AMHI, NHW, HSD, and URB, we find that there is a positive relationship between DRAPC and SCPC. However, like in Regression 1, this coefficient is not significant at any accepted alpha level. The one significant coefficient is on HSD, and it is positive. Again, this could suggest that people with high school diplomas are more likely to be arrested for drug crimes in Mississippi. An alternative reason for this positive coefficient could be that people with high school diplomas live in areas with a higher law enforcement budget, which could increase the number of drug-related arrests per capita. The R² value of this regression is much higher than for Regression 1 (0.537 vs. 0.0024), meaning that the addition of demographic control variables helps explain much more of the cross-sectional variation in DRAPC than SCPC. Lastly, the p-value(F) is much smaller than the p-value on HSD, meaning that, even though none of the other independent variables have statistically significant coefficients separately, there must be some significant effect of at least one of those variables on DRAPC.

(3) Regression 3 contains a negative coefficient on SCPC. This sign switch on the coefficient may be due to the fact that the correlation between DRAPC_t and DRAPC_{t-1} is highly positive. Controlling for DRAPC_{t-1}, the coefficient on SCPC is now negative. However, the coefficient on SCPC is still not statistically significant, so it cannot be concluded that there is any effect of SCPC on DRAPC from this regression. The R² value of this regression is even higher than in Regression 2, meaning that the addition of a lagged dependent variable helps explain more of the cross-sectional variation of DRAPC, even without the demographic control variables. The p-value(F) is statistically significant in this regression; however, this is not surprising, as the p-value on DRAPC_{t-1} (not shown in the table) is incredibly small, at 7.59e-13.

(4) Regression 4 contains an even smaller negative coefficient on SCPC than Regression 3. However, again, this coefficient is not statistically significant. In this regression, the only statistically significant coefficient is on NHW, and that coefficient is positive, meaning that a higher percentage of residents who identify as non-Hispanic Whites in an area leads to a higher number of drug-related arrests per capita. Again, this might be surprising since it suggests that non-Hispanic Whites are arrested for drug crimes more often than other races. However, it could also be due to the fact that non-Hispanic whites are wealthier in Mississippi on average, and higher-income areas could lead to higher law enforcement budgets. The R² value of this regression is higher than that of Regression 3, which could mean that introduction of demographic control variables helps explain more of the cross-sectional variation in DRAPC. Lastly, the p-value(F) of this regression is very small, much smaller than the p-value on NHW, meaning that some of the other coefficients may actually be statistically significant. However, this small p-value on this F-statistic may simply reflect the lagged dependent variable.
(5) Regression 5 contains the largest negative coefficient on SCPC of any of the regressions in Table 3.1. However, this coefficient is not statistically significant. The R^2 value of this regression is higher than that of Regression 4, indicating that the use of a fixed-effects model helps explain more of the variation in DRAPC than any previous regression, even without the use of demographic control variables.

(6) Regression 6 also contains a negative coefficient on SCPC, though not as large as the one in Regression 5. Again, this coefficient is not statistically significant. The only statistically significant coefficient is on NHW. However, as opposed to Regression 4, this coefficient is negative, meaning an increase in the percentage of residents who identify as non-Hispanic Whites in a district leads to a smaller number of drug-related arrests per capita. This could simply be interpreted as meaning non-Hispanic Whites are less likely to be arrested for drug-related offenses. This does not necessarily mean that non-Hispanic Whites commit fewer drug-related crimes than other racial groups, but rather that they are less likely to be caught doing those crimes. The R^2 value of this regression is the highest of any regression in Table 3.1, indicating that this regression explains the most variation of DRAPC out of any of the regressions in Table 3.1. Lastly, the p-value(F) of this regression is statistically significant, but is larger than the p-value on the coefficient on NHW, meaning that it is unlikely that any other independent variable in this regression is statistically significant.

An additional analysis that could be done is an OLS model with fixed effects, robust standard errors, the control variables, and a lag of DRAPC. However, not enough data has been collected to perform this analysis; at least one additional year of data is required. Additionally, the fact that the coefficient on NHW is positive in Regression 4 and negative in Regression 6 may mean that there are not enough years of data to justify using either a lagged dependent variable or a fixed-effects model at all.

**Discussion of Initial Findings**

The initial regression analysis conducted shows a positive but insignificant relationship between SCPC and DRAPC. A positive coefficient on SCPC in Regression 1 can be interpreted as meaning an increase in the number of successful intervention court completions per capita is correlated with an increase in the number of drug-related arrests per capita. One explanation for this result is that there is a degree of reverse causality in this regression. This would mean that an increase in successful intervention court completions per capita does not increase the number of drug-related arrests per capita; rather, an increase in drug-related arrests per capita precipitates the need for intervention courts, so successful intervention court completions per capita increases. To attempt to reduce the degree of reverse-causality in the regression, demographic control variables were included for income (average of median household income weighted by county), race (percentage of non-Hispanic white residents weighted by county), education
(percentage of residents with a high-school diploma weighted by county), and urbanization (percentage of residents who live in urban areas) for each circuit court district. However, after the introduction of control variables (Table 4.1), the coefficient on SCPC actually increased but remained insignificant. An increase in the coefficient on SCPC does not support the theory that there is reverse-causality in the regression, as we would expect the coefficient on SCPC to decrease when controls are added if there is a degree of the reverse causality present. However, given that the coefficient on SCPC is statistically insignificant in both Regressions 1 and 2, it cannot be concluded from those regressions that there is any effect of SCPC on DRAPC.

Given that the coefficients on SCPC in Regressions 1 and 2 are statistically insignificant, it is still possible that a degree of reverse-causality is present in these regressions. To attempt to reduce the possible reverse-causality, a lag of DRAPC was introduced to control for inertia in the data, given that DRAPC_\(t\) is highly correlated with DRAPC_\(t-1\). The resulting model (Regression 3) contained a negative coefficient on SCPC and, when controls were added to this regression (Regression 4), the coefficient was even more negative. This would mean that an increase in the number of successful intervention court completions per capita does reduce the number of drug-related arrests per capita. However, the coefficient on SCPC for Regressions 3 and 4 are also statistically insignificant. Regressions 5 and 6 continue to reduce the coefficients on SCPC, but these coefficients are also statistically insignificant. Also, given the fact that the coefficient on NHW is positive in Regression 4 and negative in Regression 6, there are not enough years of data to justify using either a lagged dependent variable or a fixed-effects model. Given that there is no model presented in this paper so far that contains a statistically significant, negative coefficient on SCPC, it cannot be stated that an increase in the number of successful intervention court completions per capita causes a decrease in drug-related arrests per capita.

In retrospect, this is unsurprising, given that the number of successful intervention court completions only explains 0.24% of the variation in drug-related arrests, as shown in Regression 1. One reason for this low goodness of fit could be that the number of successful intervention court completions in Mississippi from 2018 to 2020 totals only about 3% of the total number of drug-related arrests in Mississippi over the same time period, so we would not expect successful intervention court completions per capita to have much effect on drug-related arrests per capita. Alternatively, it could be that the only correlation between DRAPC and SCPC comes from the fact that an increasing number of drug-related arrests per capita increases the number of successful intervention court completions per capita solely because there are now more offenders that are eligible for the program.
Chapter 5: When Are Intervention Courts Used?

Because it cannot be determined whether the number of successful intervention court completions has any effect on the number of drug-related arrests, this chapter explores the reverse relationship, i.e., whether the number of drug-related arrests or demographic control variables have any effect on the use of intervention courts. Three additional sets of regressions are performed in this chapter. The first regresses the intervention court participation rate (denoted as NCPperDRA) on the number of drug-related arrests per capita and/or demographic control variables to determine the change in the percentage of drug-related arrests that end in the offender going through an intervention court program. The second regresses the intervention court completion rate (denoted as SCperICE) on the number of drug-related arrests per capita and/or demographic control variables, to determine the effect that rising drug-related arrests have on the percentage of intervention court participants who graduate from the program. A final set of regressions regresses the delay in the adoption of intervention courts, compared to the initial intervention court adoption, (denoted as Delay), on demographic control variables to determine how demographic characteristics in a district circuit court affect the adoption of intervention courts.

Descriptive Statistics

The following figure (Figure 5.1) shows the summary statistics for the new variables introduced in this section.

**Figure 5.1: Additional Summary Statistics**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>Median</th>
<th>S.D.</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>ICEPC</td>
<td>0.02726</td>
<td>0.02275</td>
<td>0.01625</td>
<td>0.004766</td>
<td>0.07251</td>
</tr>
<tr>
<td>NCPPC</td>
<td>0.03371</td>
<td>0.03060</td>
<td>0.02099</td>
<td>0.001948</td>
<td>0.09359</td>
</tr>
<tr>
<td>NCPperDRA</td>
<td>10.18</td>
<td>5.818</td>
<td>9.432</td>
<td>2.193</td>
<td>34.09</td>
</tr>
<tr>
<td>SCperICE</td>
<td>52.69</td>
<td>56.19</td>
<td>22.18</td>
<td>0.000</td>
<td>87.50</td>
</tr>
<tr>
<td>Delay</td>
<td>6.794</td>
<td>6.000</td>
<td>4.559</td>
<td>0.000</td>
<td>14.00</td>
</tr>
</tbody>
</table>

ICEPC denotes intervention court exits per capita, NCPPC denotes new intervention court participants per capita, NCPperDRA denotes the intervention court participation rate by circuit court district, SCperICE denotes the intervention court completion rate by circuit court district, and Delay denotes the delay in intervention court adoption.

The next figure (Figure 5.2) shows a correlation matrix between the new variables introduced in this section and DRAPC and the demographic control variables.
Figure 5.2: Additional Correlation Matrix

<table>
<thead>
<tr>
<th>NCPperDRA</th>
<th>SCperICE</th>
<th>Delay</th>
</tr>
</thead>
<tbody>
<tr>
<td>-0.6729</td>
<td>-0.0203</td>
<td>-0.1691 DRAPC</td>
</tr>
<tr>
<td>-0.4001</td>
<td>-0.1174</td>
<td>0.2713 AMHI</td>
</tr>
<tr>
<td>-0.4609</td>
<td>-0.3348</td>
<td>0.2631 NHW</td>
</tr>
<tr>
<td>-0.4832</td>
<td>-0.2417</td>
<td>-0.1310 HSD</td>
</tr>
<tr>
<td>-0.1406</td>
<td>0.1082</td>
<td>-0.4428 URB</td>
</tr>
<tr>
<td>1.0000</td>
<td>-0.0957</td>
<td>0.2378 NCPperDRA</td>
</tr>
<tr>
<td>1.0000</td>
<td>0.1000</td>
<td>0.1389 SCperICE</td>
</tr>
<tr>
<td></td>
<td></td>
<td>1.0000 Delay</td>
</tr>
</tbody>
</table>

ICEPC denotes intervention court exits per capita, NCPPC denotes new intervention court participants per capita, NCPperDRA denotes new intervention court participants per capita as a percentage of drug-related arrests per capita, SCperICE denotes successful intervention court completions as a percentage of intervention court exits, and Delay denotes the delay in the adoption of intervention courts.

Intervention court participation (NCPperDRA) is negatively correlated with many of the variables in the following regressions, with the highest negative correlation existing between it and DRAPC. This highly-negative correlation means that, when the number of drug-related arrests increases, the intervention court participation rate decreases by a significant amount. One possible explanation for this relationship could be that intervention courts only have a certain capacity of participants they can have at any one time. Thus, the intervention court participation rate decreases when drug-related arrests per capita increase due to the fact that DRA is in the denominator of the dependent variable. Therefore, this relationship makes sense.

The intervention court completion rate (SCperICE) is negatively correlated with every other variable in this correlation matrix except for URB and Delay. The variable that is the most highly negatively correlated with intervention court completion percentage is NHW, meaning that areas with a higher number of non-Hispanic Whites have a lower intervention court completion percentage. One reason for this correlation could be due to the fact that non-Hispanic Whites have higher income on average than other races (per the correlation coefficient between NHW and AMHI in Figure 3.3 above), and, according to Judge Starrett, the “trust-fund babies” are usually less likely to succeed in an intervention court program.

The variable that is most highly correlated with Delay is URB, and the correlation coefficient between the two means that more urban areas adopted intervention courts earlier than more rural areas. Another interesting correlation coefficient exists between Delay and NCPperDRA. Presumably, districts that are more supportive of intervention court programs would adopt them sooner and use them more often. Therefore, we should expect that NCPperDRA and Delay would be negatively correlated. However, the correlation coefficient that exists between these two variables is positive, at 0.2378. This means that districts that adopted intervention courts sooner have a lower participation rate today than districts that took more time to adopt
intervention courts. I would expect that intervention court programs that have been around longer would be more capable of accommodating a higher number of program participants, so this correlation coefficient is surprising. One possible reason for this positive correlation could be that districts that adopted intervention courts sooner than others have worse drug problems, and prefer to make the intervention court more exclusive to high-risk offenders.

**Effect of Drug-Related Arrests on New Intervention Court Participant Rates**

The first set of regressions looks at the effect of DRAPC on the intervention court participation rate (denoted as NCPperDRA). I would expect that an increase in drug-related arrests would decrease intervention court participation, given that intervention courts only have so much capacity to accept new participants. The intervention court participation rate is found by dividing the number of new intervention court participants per capita by the number of drug-related arrests. The total number of new intervention court participants in 2020 in Mississippi was 904, while the total number of drug-related arrests in Mississippi during the same period was 16523. The percentage of drug-related arrests in Mississippi that end in the offender being placed in an intervention court program is higher than the percentage of drug-related arrests in Mississippi that end in the offender graduating from an intervention court program (about 5.5% vs. about 3%). Therefore, it can be expected that the effect of DRAPC on the intervention court participation rate is likely more significant than the effect on successful intervention court completions as a percentage of drug-related arrests. Additionally, demographic control variables are added to these regressions to see how income, racial composition, education level, and level of urbanization affect intervention court participation and completion percentages.

I was able to collect data on the number of new intervention court participants (NCP) from the same Mississippi Supreme Court Annual Report that I used to collect the number of successful intervention court completions. Unfortunately, data on NCP was only available for 2020, so only one year of data is used in this set of regressions, meaning that each regression only contains 22 observations. To control for the cross-sectional variation in a population that could skew the results of the regression, I divided the number of NCPs by the total population in each circuit court district to get NCPPC, the intervention court participants per capita for each circuit court district.

Regression 7 regresses the intervention court participation rate on the number of drug-related arrests per capita. Regression 8 adds demographic control variables to Regression 7 as independent variables. Because only one year of data is available for these analyses, it is not possible to incorporate a lagged dependent variable into the regression or to perform a fixed-effects analysis. A summary table of the results is shown in Table 5.1.
Table 5.1:

<table>
<thead>
<tr>
<th>NCPperDRA on DRAPC</th>
<th>Coefficient on DRAPC</th>
<th>Coefficient on AMHI</th>
<th>Coefficient on NHW</th>
<th>Coefficient on HSD</th>
<th>Coefficient on URB</th>
<th>R-squared value</th>
<th>Number of Obs.</th>
<th>P-value(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(7) OLS with No Controls</td>
<td>-24.66 (-0.753 (0.003***))</td>
<td>-0.003</td>
<td>-0.138</td>
<td>-0.396</td>
<td>-0.061</td>
<td>0.453</td>
<td>22</td>
<td>0.003***</td>
</tr>
<tr>
<td>(8) OLS with Controls</td>
<td>-21.88 (0.0064**)</td>
<td>0.292 (0.219)</td>
<td>-0.232 (0.519)</td>
<td>-0.162 (0.712)</td>
<td>-0.1273 (0.762)</td>
<td>0.494</td>
<td>22</td>
<td>0.096*</td>
</tr>
</tbody>
</table>

The first column in the above table specifies which regression is being summarized in that row. The number in parentheses before the regression description indicates the regression number. OLS indicates an ordinary least squares regression. “Controls” refer to demographic control variables. Numbers in columns 2-6 show the coefficient on the variable (the top value), the coefficient for the normalized regression (the middle value), and the p-value associated with that coefficient (the bottom value). The final column in this table shows the p-value of the F-statistic for the regression, denoted as p-value(F). P-values with three asterisks (***) indicate that the coefficient on that variable is statistically significant at an alpha level of 0.01. Two asterisks (**) and one asterisk (*) indicate that the coefficient on that variable is statistically significant at alpha levels of 0.05 and 0.1, respectively. DRAPC denotes drug-related arrests per capita, NCPperDRA denotes the intervention court participation rate, AMHI denotes the average of county-level median household incomes, NHW denotes the percentage of residents who identify as non-Hispanic Whites, HSD denotes the percentage of residents who have obtained a high school diploma, and URB denotes the percentage of residents who live in urbanized areas.

(7) Regression 7 contains a statistically significant, negative coefficient on DRAPC of -24.66, meaning that an increase of one percentage point in drug-related arrests per capita decreases the percent of intervention court participation for that year by almost 25 percentage points. Granted, a one percentage point increase in DRAPC would mean that drug-related arrests in the average district circuit court would more than triple in number. The R² value of this regression is not small, at 0.453, meaning that the number of drug-related arrests in Mississippi explains 45.3% of the variation in intervention court participation.

(8) Regression 8 contains a slightly smaller, statistically significant, negative coefficient on DRAPC of -21.88. None of the demographic control variables, however, have statistically significant coefficients. In addition, the p-value(F) of this regression is larger than the p-value of the coefficient on DRAPC, so it is unlikely that any of the demographic control variables' coefficients would have any significance on their own. However, the R² value is slightly higher in this regression, so the demographic control variables do help explain some of the cross-sectional variation in the intervention court participation rate.

Each of these regressions contains a large, negative, statistically significant coefficient on DRAPC. That means we can say, based on these regressions, that the intervention court participation rate decreases when drug-related arrests per capita increase.
Effect of Drug-Related Arrests on Successful Intervention Court Completion Rates

The next set of regressions (see Table 5.2) looks at how the number of drug-related arrests affects the effectiveness of DTC programs. An increase in the number of drug-related arrests would increase the pool of potential intervention court participants. The expectation is that this could decrease the percentage of intervention court participants who graduate from the program, given a constant number of intervention court participants, by making the selection process favor high-risk offenders who may be less likely to succeed, but may be much more important to the success of the program.

These regressions incorporate a new variable, intervention court exits per capita (ICEPC), as the denominator of the independent variable. This variable measures the number of intervention court participants who left the program either through successful completion or incarceration. The number of participants who were incarcerated as a result of leaving the program was found on the 2020 Mississippi Supreme Court Annual Report and was added to the number of successful completions for each circuit court district to get ICE, the number of intervention court exits. ICE for each circuit court district was then divided by the population in that district to get intervention court exits per capita.

This set of regressions uses the intervention court completion rate as the dependent variable. The intervention court completion rate equals the number of successful intervention court completions divided by the number of intervention court exits and is denoted by SCperICE. Regression 9 regresses intervention court completion percentage (SCperICE) on the number of drug-related arrests per capita using ordinary least squares. Regression 10 adds the demographic control variables as independent variables to Regression 9. Because regressions 1-6 did not show any effect of successful intervention court completions per capita, it is likely that even with additional controls added to those regressions we would not see any effect of SCPC on DRAPC. Because only one year of data is available for these analyses, it is not possible to incorporate a lagged dependent variable control into the regression or to perform a fixed-effects analysis.
Table 5.2:

<table>
<thead>
<tr>
<th>SCperICE (on DRAPC)</th>
<th>Coefficient (on DRAPC)</th>
<th>Coefficient (on AMHI)</th>
<th>Coefficient (on NHW)</th>
<th>Coefficient (on HSD)</th>
<th>Coefficient (on URB)</th>
<th>R-squared Value</th>
<th>Number of Obs</th>
<th>P-value(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(9) OLS with No Controls</td>
<td>-1.75 (-0.0227)</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>0.000412</td>
<td>22</td>
<td>0.936</td>
</tr>
<tr>
<td>(10) OLS with Controls</td>
<td>33.05 (0.429)</td>
<td>0.0011 (0.425)</td>
<td>-0.688 (0.4918)</td>
<td>-3.687 (0.6403)</td>
<td>0.224 (0.2002)</td>
<td>0.284</td>
<td>22</td>
<td>0.206</td>
</tr>
</tbody>
</table>

The first column in the above table specifies which regression is being summarized in that row. The number in parentheses before the regression description indicates the regression number. OLS indicates an ordinary least squares regression. “Controls” refer to demographic control variables. Numbers in columns 2-6 show the coefficient on the variable (the top value), the coefficient for the normalized regression (the middle value), and the p-value associated with that coefficient (the bottom value). The final column in this table shows the p-value of the F-statistic for the regression, denoted as p-value(F). P-values with three asterisks (**) indicate that the coefficient on that variable is statistically significant at an alpha level of 0.01. Two asterisks (*) and one asterisk (*) indicate that the coefficient on that variable is statistically significant at alpha levels of 0.05 and 0.1, respectively. SCperICE denotes the intervention court completion rate, DRAPC denotes drug-related arrests per capita, AMHI denotes the average of county-level median household incomes, NHW denotes the percentage of residents who identify as non-Hispanic Whites, HSD denotes the percentage of residents who have obtained a high school diploma, and URB denotes the percentage of residents who live in urbanized areas.

(9) Regression 9 contains a negative coefficient on DRAPC, which would mean that an increasing number of drug-related arrests per capita decreases the average completion rate for DTCs in Mississippi if the coefficient were statistically significant. However, given that the coefficient has an incredibly large p-value of 0.936, it is statistically insignificant. Additionally, the R^2 value is very small, meaning that the number of drug-related arrests does not explain much of the cross-sectional variation in intervention court completion percentage at all.

(10) Regression 10 contains a very large positive coefficient on DRAPC compared to regression 8. However, again, this coefficient is not statistically significant. Likewise, none of the demographic control variables have statistically significant coefficients. They do help explain more of the cross-sectional variation in SCperICE, as the R^2 of this regression is higher than Regression 9, but still small.

Given that neither of these regressions has any statistically significant p-values or statistically significant p-value(F)s, it cannot be stated as to whether or not the number of drug-related arrests per capita affects the completion percentage for intervention court participants in Mississippi.
Explaining the Delay in Intervention Court Adoption Using Demographic Controls

The first intervention court in Mississippi was started in the 14th Judicial Circuit Court in 1999. Since then, an intervention court has been established in each of the 21 other Judicial Circuit Courts. An interesting question to ask is how the demographic characteristics of circuit court districts affected the time it took for the Judicial Circuit Court to adopt an intervention court. The best way to answer this question would be to regress the delay of adoption compared to the first intervention court on the demographic characteristics for the year that the corresponding intervention court was founded. However, since the newest intervention court that I have data on was founded in 2013, and I only have demographic characteristic data going back to 2018, this is not possible. Instead, I regressed the delay of adoption from the first intervention court on the 2018 demographic characteristic values. I was only able to obtain the year of adoption for 17 of the 22 intervention courts, as this information is not readily available online and I have not heard back from the remaining five intervention courts yet regarding the year they were founded. A summary of this regression is given in Table 5.3.

Table 5.3

<table>
<thead>
<tr>
<th>Delay on Controls</th>
<th>Coefficient on AMHI</th>
<th>Coefficient on NHW</th>
<th>Coefficient on HSD</th>
<th>Coefficient on URB</th>
<th>R-squared value</th>
<th>Number of Obs.</th>
<th>P-value(F)</th>
</tr>
</thead>
<tbody>
<tr>
<td>(11) OLS</td>
<td>0.0004</td>
<td>-0.076</td>
<td>-0.108</td>
<td>-0.141</td>
<td>0.4042</td>
<td>17</td>
<td>0.004***</td>
</tr>
<tr>
<td></td>
<td>(0.694)</td>
<td>(0.266)</td>
<td>(0.0912)</td>
<td>(0.6133)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.0743*)</td>
<td>(0.4014)</td>
<td>(0.8373)</td>
<td>(0.085*)</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

The first column in the above table specifies which regression is being summarized in that row. The number in parentheses before the regression description indicates the regression number. OLS indicates an ordinary least squares regression. “Controls” refer to demographic control variables. Numbers in columns 2-6 show the coefficient on the variable (the top value), the coefficient for the normalized regression (the middle value), and the p-value associated with that coefficient (the bottom value). The final column in this table shows the p-value of the F-statistic for the regression, denoted as p-value(F). P-values with three asterisks (**) indicate that the coefficient on that variable is statistically significant at an alpha level of 0.01. Two asterisks (**) and one asterisk (*) indicate that the coefficient on that variable is statistically significant at alpha levels of 0.05 and 0.1, respectively. Delay denotes delay in the adoption of intervention court, AMHI denotes the average of county-level median household incomes, NHW denotes the percentage of residents who identify as non-Hispanic Whites, HSD denotes the percentage of residents who have obtained a high school diploma, and URB denotes the percentage of residents who live in urbanized areas.

There are two variables with statistically significant coefficients in this regression: AMHI and URB. The interpretation of the coefficient on AMHI is that circuit court districts with higher income took longer to adopt intervention courts. One possible explanation for this is that districts with higher income may be less likely to adopt intervention courts due to the political leanings of the area. The interpretation of the coefficient on URB is that circuit court districts with a higher percentage of residents living in urban areas took less time to adopt an intervention
court. One possible reason for this is that it may be more difficult to implement intervention courts in areas with low concentrations of people. The $R^2$ value of 0.4042 in this regression means that the demographic variables help to explain 40.42% of the cross-sectional variation in Delay.

Chapter 6: Conclusion

Intervention courts were implemented in Mississippi to reduce drug crime recidivism, save the state money by not incarcerating non-violent drug offenders, and improve the lives of drug addicts and drug abusers across the state. They started out serving the “low hanging fruit”, or offenders with a low risk of recidivation and a high chance of graduation, but have now moved on to serving those high-risk offenders who need more help in becoming clean than anybody else. There are many key components of a successful intervention court. One of those components is good data collection practices and periodic analyses of intervention court effectiveness. This paper sought to gauge the effectiveness of Mississippi intervention courts through data collection and analysis.

Before performing the regression analyses, I expected that an increase in successful intervention court completions would decrease the number of drug-related arrests. For my first set of regressions, I regressed drug-related arrests per capita on successful intervention court completions per capita and demographic variables including household income, racial composition, education level, and level of urbanization, using ordinary least squares, lagged-dependent variable, and fixed-effects methods. The OLS regressions contained positive coefficients on SCPC, which was the opposite of what I expected. This meant one of two things: that there was a degree of reverse causality in my regressions or that an increase in SCPC increases the number of DRAPC. To attempt to reduce the possible degree of reverse-causality in these regressions, I first added a lag of DRAPC and then used a fixed-effects model. Both of these models produced negative coefficients on SCPC with and without demographic control variables. However, the coefficients on SCPC were not statistically significant in any of these regressions, and very few coefficients on the demographic characteristic variables were statistically significant. It could not be concluded that there was any effect of SCPC on DRAPC. Given that there were only three years of data on these variables, it is possible that with a few additional years of data, more coefficients could be statistically significant and an effect of SCPC on DRAPC could be observed.

Next, I decided to see how the number of drug-related arrests per capita affects the intervention court participation rate by regressing NCPperDRA on DRAPC and demographic control variables. With no demographic control variables present, a statistically significant, large, negative coefficient on DRAPC was produced. With demographic control variables present, the
effect was still large and negative, but not quite as large. This means that an increased number of drug-related arrests drastically decreases the intervention court participation rate. This is most likely due to the fact that intervention courts only have a certain capacity of offenders they can allow to participate at any one time. If intervention courts wish to be prepared for possible increases in drug-related arrests in the future, a good measure they could take would be to increase the amount of staff at their courts to better handle an increased number of drug-addicted or drug-abusing offenders who need the help that intervention courts provide.

I then decided to see how the number of drug-related arrests per capita affects the intervention court success rate by regressing SCperICE on DRAPC and demographic control variables. Again, none of my coefficients were statistically significant, so it could not be concluded that DRAPC or any of the demographic control variables had any effect on the drug court success rate from my regressions. Given that there was only one year of data available for this set of regressions, it is possible that additional years of data could produce statistically significant coefficients on some or all of the variables in these regressions.

Finally, I wanted to see how the delay in the adoption of intervention courts is affected by demographic control variables. I found that areas with a higher average income took longer to adopt intervention courts and that areas with a higher percentage of residents living in urban areas adopted intervention courts more quickly.

While many of the regressions performed in this paper did not produce very many statistically significant coefficients, there is certainly a possibility for future research to obtain statistically significant coefficients on these regressions. Some ways that this could be done are:

1. The use of an instrumental variable to completely get rid of any degree of reverse-causality.
2. An analysis of many individual intervention court participants that includes recidivism follow-ups at certain time frames in the future rather than an analysis of aggregate intervention court data.
3. Additional demographic control variables could explain more of the cross-sectional variation in the dependent variables.
4. Additional years of data to provide more observations.

If some or all of these measures are taken, it is possible that future research could be able to reach a conclusion on the effect of successful intervention court completions on drug-related arrests in Mississippi, the effect of drug-related arrests on intervention court completion rates in Mississippi, and the effect of other demographic control variables on the delay in adoption of intervention court programs by districts.
Appendix:

Regression 2:
Model 2: Pooled OLS, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: DRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>-3.49682</td>
<td>0.994441</td>
<td>-3.516</td>
<td>0.0021 ***</td>
</tr>
<tr>
<td>SCPC</td>
<td>2.81269</td>
<td>2.75800</td>
<td>1.020</td>
<td>0.3194</td>
</tr>
<tr>
<td>AMHI</td>
<td>5.8346e-06</td>
<td>8.66258e-06</td>
<td>0.6735</td>
<td>0.5079</td>
</tr>
<tr>
<td>NHW</td>
<td>0.000719256</td>
<td>0.00375807</td>
<td>0.1914</td>
<td>0.8501</td>
</tr>
<tr>
<td>HSD</td>
<td>0.0443279</td>
<td>0.0141687</td>
<td>3.129</td>
<td>0.0051 ***</td>
</tr>
<tr>
<td>URB</td>
<td>-0.000937017</td>
<td>0.00220200</td>
<td>-0.4255</td>
<td>0.6748</td>
</tr>
</tbody>
</table>

Mean dependent var 0.485200 S.D. dependent var 0.287936
Sum squared resid 2.49319 S.E. of regression 0.203843
R-squared 0.537367 Adjusted R-squared 0.498814
F(5, 21) 19.08240 P-value(F) 3.58e-07
Log-likelihood 14.46202 Akaike criterion -16.92404
Schwarz criterion -3.786108 Hannan-Quinn -11.73262
rho 0.681014 Durbin-Watson 0.425781

Normalized Regression 2:
Model 3: Pooled OLS, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: NormalizedDRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th></th>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>const</td>
<td>8.44796e-06</td>
<td>0.131845</td>
<td>6.407e-05</td>
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<tr>
<td>NormalizedSCPC</td>
<td>0.118128</td>
<td>0.115831</td>
<td>1.020</td>
<td>0.3194</td>
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<tr>
<td>NormalizedAMHI</td>
<td>0.178135</td>
<td>0.264474</td>
<td>0.6735</td>
<td>0.5079</td>
</tr>
<tr>
<td>NormalizedNHW</td>
<td>0.0395798</td>
<td>0.206802</td>
<td>0.1914</td>
<td>0.8501</td>
</tr>
<tr>
<td>NormalizedHSD</td>
<td>0.593133</td>
<td>0.189585</td>
<td>3.129</td>
<td>0.0051 ***</td>
</tr>
<tr>
<td>NormalizedURB</td>
<td>-0.0645570</td>
<td>0.151709</td>
<td>-0.4255</td>
<td>0.6748</td>
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</table>

Mean dependent var 1.30e-06 S.D. dependent var 0.999988
Sum squared resid 30.07039 S.E. of regression 0.707936
R-squared 0.537367 Adjusted R-squared 0.498814
F(5, 21) 19.08240 P-value(F) 3.58e-07
Log-likelihood -67.70819 Akaike criterion 147.4164
Schwarz criterion 160.5543 Hannan-Quinn 152.6078
rho 0.681014 Durbin-Watson 0.425781
Regression 3:
Model 4: Pooled OLS, using 44 observations
Included 22 cross-sectional units
Time-series length = 2
Dependent variable: DRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
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</thead>
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<tr>
<td>const</td>
<td>0.103445</td>
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<td>SCPC</td>
<td>-0.597697</td>
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</tr>
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<td>DRAPC_{t-1}</td>
<td>0.812709</td>
<td>0.0532113</td>
<td>15.27</td>
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</tbody>
</table>

Mean dependent var 0.486803 S.D. dependent var 0.276426
Sum squared resid 0.652487 S.E. of regression 0.126152
R-squared 0.801415 Adjusted R-squared 0.791728
F(2, 21) 158.2377 P-value(F) 2.17e-13
Log-likelihood 30.21208 Akaike criterion -54.42417
Schwarz criterion -49.07160 Hannan-Quinn -52.43918
rho -0.206571 Durbin-Watson 1.118025

Normalized Regression 3:
Model 5: Pooled OLS, using 44 observations
Included 22 cross-sectional units
Time-series length = 2
Dependent variable: NormalizedDRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
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<td>const</td>
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<td>NormalizedSCPC</td>
<td>-0.0251023</td>
<td>0.0607721</td>
<td>-0.4131</td>
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<tr>
<td>NormalizedDRAPC_{t-1}</td>
<td>0.812709</td>
<td>0.0532113</td>
<td>15.27</td>
</tr>
</tbody>
</table>

Mean dependent var 0.005566 S.D. dependent var 0.960012
Sum squared resid 7.869876 S.E. of regression 0.438119
R-squared 0.801415 Adjusted R-squared 0.791728
F(2, 21) 158.2377 P-value(F) 2.17e-13
Log-likelihood -24.56805 Akaike criterion 55.13611
Schwarz criterion 60.48868 Hannan-Quinn 57.12110
rho -0.206571 Durbin-Watson 1.118025
### Regression 4:
Model 6: Pooled OLS, using 44 observations
Included 22 cross-sectional units
Time-series length = 2
Dependent variable: DRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
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<td>SCPC</td>
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<td>AMHI</td>
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<td>1.94518e-06</td>
<td>0.7923</td>
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<tr>
<td>NHW</td>
<td>0.00402362</td>
<td>0.00148208</td>
<td>2.715</td>
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<td>HSD</td>
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<td>0.00944085</td>
<td>-1.301</td>
</tr>
<tr>
<td>URB</td>
<td>0.000195325</td>
<td>0.000945397</td>
<td>0.2066</td>
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<td>DRAPC _t-1</td>
<td>0.805252</td>
<td>0.0888497</td>
<td>9.063</td>
</tr>
</tbody>
</table>

Mean dependent var 0.486803
S.D. dependent var 0.276426
Sum squared resid 0.509205
S.E. of regression 0.117313
R-squared 0.845023
Adjusted R-squared 0.819892
F(6, 21) 66.15442
P-value(F) 1.51e-12
Log-likelihood 35.66680
Akaike criterion 57.33360
Schwarz criterion 44.84427
Hannan-Quinn criterion 52.70195
rho 0.743282
Durbin-Watson 1.417866

### Normalized Regression 4:
Model 7: Pooled OLS, using 44 observations
Included 22 cross-sectional units
Time-series length = 2
Dependent variable: NormalizedDRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
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<td>-0.7634</td>
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<tr>
<td>NormalizedAMHI</td>
<td>0.0470527</td>
<td>0.0593876</td>
<td>0.7923</td>
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<tr>
<td>NormalizedNHW</td>
<td>0.221415</td>
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<td>NormalizedHSD</td>
<td>-0.164361</td>
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<tr>
<td>NormalizedURB</td>
<td>0.0134572</td>
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<td>NormalizedDRAPC _t-1</td>
<td>0.805252</td>
<td>0.0888497</td>
<td>9.063</td>
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</table>

Mean dependent var 0.005566
S.D. dependent var 0.960012
Sum squared resid 6.141695
S.E. of regression 0.407421
R-squared 0.845023
Adjusted R-squared 0.819892
F(6, 21) 66.15442
P-value(F) 1.51e-12
Log-likelihood -19.11334
Akaike criterion -57.33360
Schwarz criterion -64.71601
Hannan-Quinn criterion -52.70195
rho 0.743282
Durbin-Watson 1.417866
Regression 5:
Model 8: Fixed-effects, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: DRAPC
Robust (HAC) standard errors

<table>
<thead>
<tr>
<th>coefficient</th>
<th>std. error</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
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Mean dependent var 0.485200 S.D. dependent var 0.287936
Sum squared resid 0.514389 S.E. of regression 0.109373
LSDV R-squared 0.904548 Within R-squared 0.033358
Log-likelihood 66.54626 Akaike criterion -87.09253
Schwarz criterion -67.73047 Hannan-Quinn -67.19209
rho -0.396871 Durbin-Watson 1.529075

Joint test on named regressors -
Test statistic: F(1, 21) = 2.32866
with p-value = P(F(1, 21) > 2.32866) = 0.141932

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(21, 15.4) = 85.9996
with p-value = P(F(21, 15.4) > 85.9996) = 2.56553e-12
Normalized Regression 5:
Model 9: Fixed-effects, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: NormalizedDRAFC
Robust (HAC) standard errors

<table>
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<tr>
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<td>6.82e-12 ***</td>
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<tr>
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<td>-0.0915858</td>
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Mean dependent var  1.30e-06  S.D. dependent var  0.999988
Sum squared resid   6.204225  S.E. of regression  0.379848
LSDV R-squared      0.904548  Within R-squared  0.033358
Log-likelihood      -15.62394 Akaike criterion  77.24789
Schwarz criterion   127.6099  Hannan-Quinn      97.14833
rho                 -0.396871  Durbin-Watson    1.529075

Joint test on named regressors -
Test statistic: F(1, 21) = 2.32866
with p-value = P(F(1, 21) > 2.32866) = 0.141932

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(21, 15.4) = 85.9996
with p-value = P(F(21, 15.4) > 85.9996) = 2.56553e-12
Regression 6:
Model 10: Fixed-effects, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: DRAPC
Robust (HAC) standard errors
Omitted due to exact collinearity: URB

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<tr>
<td>AMHI</td>
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<td>1.463</td>
<td>0.1584</td>
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<tr>
<td>NHW</td>
<td>-0.0419085</td>
<td>0.0155462</td>
<td>-2.696</td>
<td>0.0135  **</td>
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<tr>
<td>HSD</td>
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<td>0.00840825</td>
<td>-0.1945</td>
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Mean dependent var 0.485200  S.D. dependent var 0.287936
Sum squared resid  0.452213  S.E. of regression  0.106326
LSDV R-squared 0.916086  Within R-squared 0.150199
Log-likelihood 70.79754  Akaike criterion -89.59508
Schwarz criterion -32.66406  Hannan-Quinn -67.09893
rho -0.444257  Durbin-Watson 1.539884

Joint test on named regressors -
Test statistic: F(4, 21) = 3.35907
with p-value = P(F(4, 21) > 3.35907) = 0.0283097

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(21, 15.9) = 15.85
with p-value = P(F(21, 15.9) > 15.85) = 4.51411e-07
Normalized Regression 6:
Model 11: Fixed-effects, using 66 observations
Included 22 cross-sectional units
Time-series length = 3
Dependent variable: NormalizedDRAFC
Robust (HAC) standard errors
Omitted due to exact collinearity: NormalizedURB

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<td>NormalizedAMHI</td>
<td>0.295214</td>
<td>0.201845</td>
<td>1.463</td>
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<td>NormalizedNHW</td>
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<td>0.855491</td>
<td>-2.696</td>
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<td>NormalizedHSD</td>
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Mean dependent var 1.30e-06  S.D. dependent var 0.99988
Sum squared resid 5.454298  S.E. of regression 0.369266
LSDV R-squared 0.916086  Within R-squared 0.150199
Log-likelihood -11.37267  Akaike criterion 74.74533
Schwarz criterion 131.6764  Hannan-Quinn 97.24149
rho 0.444257  Durbin-Watson 1.539884

Joint test on named regressors -
Test statistic: F(4, 21) = 3.35907
with p-value = P(F(4, 21) > 3.35907) = 0.0283097

Robust test for differing group intercepts -
Null hypothesis: The groups have a common intercept
Test statistic: Welch F(21, 15.9) = 15.85
with p-value = P(F(21, 15.9) > 15.85) = 4.51411e-07
Regression 7:
Model 12: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NCPperDRA
Robust (HAC) standard errors

<table>
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<td>4.71265</td>
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<tr>
<td>DRAPC</td>
<td>-24.6565</td>
<td>7.33543</td>
<td>-3.361</td>
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Mean dependent var 10.18250 S.D. dependent var 9.432239
Sum squared resid 1022.366 S.E. of regression 7.149706
R-squared 0.452786 Adjusted R-squared 0.425425
F(1, 21) 11.29824 P-value(F) 0.002954
Log-likelihood 73.44380 Akaike criterion 150.8876
Schwarz criterion 153.0697 Hannan-Quinn 151.4016

Normalized Regression 7:
Model 13: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NormalizedNCPperDRA
Robust (HAC) standard errors

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<td>NormalizedDRAPC</td>
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<td>-3.361</td>
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Mean dependent var 0.000053 S.D. dependent var 1.000004
Sum squared resid 11.49160 S.E. of regression 0.758011
R-squared 0.452786 Adjusted R-squared 0.425425
F(1, 21) 11.29823 P-value(F) 0.002954
Log-likelihood 24.07296 Akaike criterion 52.14592
Schwarz criterion 54.32800 Hannan-Quinn 52.65995
### Regression 8:
Model 14: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NCPperDRA
Robust (HAC) standard errors

<table>
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<td>DRAPC</td>
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<td>AMHI</td>
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<td>NHW</td>
<td>-0.138296</td>
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<tr>
<td>HSD</td>
<td>-0.396238</td>
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<td>-0.3738</td>
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<td>URB</td>
<td>-0.0605323</td>
<td>0.197230</td>
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Mean dependent var 10.18250  S.D. dependent var 9.432239
Sum squared resid 946.1888  S.E. of regression 7.690046
R-squared 0.493559  Adjusted R-squared 0.335296
F(5, 21) 2.174771  P-value(F) 0.095875
Log-likelihood -72.59204  Akaike criterion 157.1841
Schwarz criterion 163.7303  Hannan-Quinn 158.7262

### Normalized Regression 8:
Model 15: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NormalizedNCPperDRA
Robust (HAC) standard errors

<table>
<thead>
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<tr>
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<td>NormalizedDRAPC</td>
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<td>NormalizedAMHI</td>
<td>0.291671</td>
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<td>NormalizedNHW</td>
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<td>NormalizedURB</td>
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Mean dependent var 0.000053  S.D. dependent var 1.000004
Sum squared resid 10.63535  S.E. of regression 0.815297
R-squared 0.493559  Adjusted R-squared 0.335296
F(5, 21) 2.174770  P-value(F) 0.095875
Log-likelihood -23.22120  Akaike criterion 58.44240
Schwarz criterion 64.98866  Hannan-Quinn 59.98450
Regression 9:
Model 16: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: SCperICE
Robust (HAC) standard errors

<table>
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<td>const</td>
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<tr>
<td>DRAPC</td>
<td>-1.74805</td>
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Mean dependent var 52.68830 S.D. dependent var 22.18145
Sum squared resid 10328.10 S.E. of regression 22.72454
R-squared 0.000412 Adjusted R-squared -0.049568
F(1, 21) 0.006699 P-value(F) 0.935543
Log-likelihood -98.88404 Akaike criterion 201.7681
Schwarz criterion 203.9502 Hannan-Quinn 202.2821

Normalized Regression 9:
Model 17: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NormalizedSCperICE
Robust (HAC) standard errors

<table>
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Mean dependent var 0.000014 S.D. dependent var 1.000020
Sum squared resid 20.99220 S.E. of regression 1.024505
R-squared 0.000412 Adjusted R-squared -0.049568
F(1, 21) 0.006699 P-value(F) 0.935543
Log-likelihood -30.70084 Akaike criterion 65.40169
Schwarz criterion 67.58377 Hannan-Quinn 65.91572
**Regression 10:**

Model 18: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: SCperICE
Robust (HAC) standard errors

<table>
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<td>DRApC</td>
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Mean dependent var | 52.68830  S.D. dependent var | 22.18145
Sum squared resid  | 7397.258   S.E. of regression  | 21.50183
R-squared          | 0.284068   Adjusted R-squared   | 0.060339
F(5, 21)           | 1.590336   P-value(F)           | 0.206220
Log-likelihood     | -95.21269  Akaike criterion     | 202.4254
Schwarz criterion  | 208.9716   Hannan-Quinn         | 203.9675

**Normalized Regression 10:**

Model 19: Pooled OLS, using 22 observations
Included 22 cross-sectional units
Time-series length = 1
Dependent variable: NormalizedSCperICE
Robust (HAC) standard errors

<table>
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<td>0.5928</td>
<td>0.5596</td>
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Mean dependent var | 0.000014  S.D. dependent var | 1.000020
Sum squared resid  | 15.03518   S.E. of regression  | 0.969380
R-squared          | 0.284068   Adjusted R-squared   | 0.060339
F(5, 21)           | 1.590336   P-value(F)           | 0.206220
Log-likelihood     | -27.02950  Akaike criterion     | 66.05900
Schwarz criterion  | 72.60525   Hannan-Quinn         | 67.60110
Regression 11:

Model 20: Pooled OLS, using 17 observations
Included 17 cross-sectional units
Time-series length = 1
Dependent variable: Delay
Robust (HAC) standard errors

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Mean dependent var 6.794118 S.D. dependent var 4.558847
Sum squared resid 198.1214 S.E. of regression 4.063264
R-squared 0.404199 Adjusted R-squared 0.205599
F(4, 16) 5.940799 P-value(F) 0.003973
Log-likelihood -44.99512 Akaike criterion 99.99024
Schwarz criterion 104.1563 Hannan-Quinn 100.4044

Normalized Regression 11:

Model 21: Pooled OLS, using 17 observations
Included 17 cross-sectional units
Time-series length = 1
Dependent variable: NormalizedDelay
Robust (HAC) standard errors

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Mean dependent var 3.87e-06 S.D. dependent var 1.000010
Sum squared resid 9.533015 S.E. of regression 0.891301
R-squared 0.404199 Adjusted R-squared 0.205599
F(4, 16) 5.940800 P-value(F) 0.003973
Log-likelihood -19.20511 Akaike criterion 48.41022
Schwarz criterion 52.57629 Hannan-Quinn 48.82434
Works Cited:


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Saint Louis Fed FRED, 2019. “Number of Residents with a High School Diploma by County in Mississippi.”


U.S. Census Bureau, 2010. “Level of Urbanization by County in Mississippi.”