EXHIBIT 1

UNITED STATES DISTRICT COURT
FOR THE SOUTHERN DISTRICT OF MISSISSIPPI
JACKSON DIVISION

LATOYA BROWN; LAWRENCE BLACKMON; HERBERT ANTHONY GREEN; KHADAFY MANNING; QUINNETTA MANNING; MARVIN MCFIELD; NICHOLAS SINGLETON; STEVEN SMITH; BESSIE THOMAS; and BETTY JEAN WILLIAMS TUCKER, individually and on behalf of a class of all others similarly situated,

Plaintiffs,

v.

MADISON COUNTY, MISSISSIPPI; SHERIFF RANDALL S. TUCKER, in his official capacity; and MADISON COUNTY SHERIFF'S DEPUTIES JOHN DOES #1 through #6, in their individual capacities,

Defendants.

Civil Action No.
3:17-cv-00347-WHB-LRA

REPORT OF BRYAN RICCHETTI, Ph.D.

March 13, 2018

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1. QUALIFICATIONS

1. I am a Vice President at Cornerstone Research and Co-Head of Cornerstone's antitrust practice. Cornerstone Research is an economic and financial consulting firm with offices in Boston, Chicago, Los Angeles, Menlo Park, New York, San Francisco, Washington, and London. I joined Cornerstone Research in 2007, after completing my Ph.D. in Economics from Cornell University. I have seventeen years of professional experience analyzing economic data related to socioeconomic and demographic characteristics (including race) and economic outcomes.

2. During my time at Cornell (2003–2007), I served as an economist at the U.S. Census Bureau analyzing government data on demographic characteristics (including race) and labor market outcomes for the U.S. population. Prior to attending Cornell, I worked at MDRC (1999–2002), a public policy think tank in New York, NY, analyzing labor market outcomes of welfare recipients, with a focus on the effect of different demographic and human capital characteristics on labor market outcomes.

3. In my work as an economic consultant at Cornerstone Research (2007 to present), I have developed particular expertise in the application of economic and statistical methods to questions that arise in the context of litigation. I have consulted on numerous discrimination matters involving statistical analysis and summary of data regarding differences between different demographic groups (including race, gender, and age) and outcomes of interest.

4. As an expert witness, I have filed two expert reports in federal court addressing issues of discrimination: one matter involving claims of age discrimination and another matter assessing the relationship between the racial distribution of entry-level police and firefighters in a given community and the racial distribution of the qualified labor pool in that community.

5. I have spoken at American Bar Association (ABA) conferences on issues related to expert testimony and statistical analysis, including serving as the testifying expert in the mock trial at both the ABA Antitrust Spring Meetings (Spring 2015) and the ABA Antitrust Law & Economics Institute for Judges (Fall 2015). I have also authored several articles that address the use of economic and statistical analysis in litigation contexts. For example, I was a co-author of the

chapter "Applying Econometrics to Assess Market Definition and Market Power" in the ABA Antitrust Section's handbook *Econometrics: Legal, Practical, and Technical Issues*.

6. My CV is attached as Appendix A to this report. My CV contains the list of my prior testimony for the last four years. I am providing my services in this matter on a pro bono basis.

2. ASSIGNMENT AND SUMMARY OF FINDINGS

2.1. Assignment

7. I have been asked by Simpson Thacher & Bartlett LLP, the American Civil Liberties Union of Mississippi Foundation, and the American Civil Liberties Union Foundation, Counsel for Plaintiffs in this action,[1] to review the available data on the locations and frequency of roadblocks implemented by the Madison County Sheriff's Department ("MCSD") in Madison County. Counsel for the Plaintiffs have also asked me to assess whether there is a relationship between the location and frequency of the roadblocks and the percentage of the population that is Black in communities where roadblocks are set up.

8. As part of my work in this matter, a team working under my supervision at Cornerstone Research has reviewed and analyzed a set of data sources produced by the MCSD in this matter that track relevant information related to roadblocks and traffic violations in Madison County. My team has also collected data from the U.S. Census Bureau that measures socioeconomic and demographic characteristics for each census tract within Madison County. I detail these data sources in Section 3 below.

9. I have also reviewed a set of relevant documents in this case, including the Complaint and the Defendants' Answer to the Complaint. Appendix B to this

[1] Class Action Complaint for Declaratory and Injunctive Relief and Individual Damages, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities,* CIVIL ACTION NO. 3:17-cv-347 WHB-LRA, filed May 8, 2017 ("Complaint").

report provides a list of the data and documents that I considered in reaching the opinions summarized in this report.

2.2. Summary of Findings

10. Based on my review of the aforementioned data sources, I have reached the following conclusions:

- The available data indicate that the MCSD implemented roadblocks at a higher rate in census tracts with a higher percentage of Black residents in Madison County. For example, there are 21 different census tracts within Madison County, each of which had a different percentage of the population that was Black over the period for which I have roadblock data (2012–2017). These 21 different census tracts allow me to examine how the frequency of roadblocks varies with the percentage of the population that is Black. As I discuss below, the racial breakdown of the 21 census tracts is split fairly cleanly into two groups—in 11 of the 21 tracts 28% or less of the population was Black during the period 2012–2017, while in the other 10 tracts 46% or more of the population was Black during the period 2012–2017. On average, the first 11 tracts were 17.6% Black and the other 10 tracts were 66.0% Black from 2012–2017.

  As I show below in Section 4, from 2012–2017 there were 14 roadblocks implemented per 1,000 residents in the 11 census tracts with the lowest percentage of Black residents (17.6% Black on average) compared to 28 roadblocks implemented per 1,000 residents in the 10 census tracts with the highest percentage of Black residents (66.0% Black on average). In other words, the number of roadblocks per person in the census tracts with a substantially larger Black percentage of the population was twice the number of roadblocks per 1,000 residents in census tracts with a relatively low Black percentage of the population. As I also show below, geocoding analysis of the locations of roadblocks corroborates this fact, showing clustering of roadblocks in substantially Black communities.

- Additionally, the differences in the rates of roadblocks in communities with a higher percentage of Black residents are not fully explained by differences in the frequency of DUI arrests and traffic violations (arrests and citations) issued by the MCSD. For example, Defendants contend that regulating drunken driving and traffic violations are relevant criteria used in deciding where to implement a roadblock. Although Defendants' data indicate that there are, on average, higher rates of DUI arrests and traffic violations in census tracts with a higher percentage of Black residents, I show below that such criteria do not fully explain the higher rates of roadblocks in these census tracts. For example, from 2012–2017 the rate of roadblocks per 100 DUI arrests in the 10 tracts with the highest Black percentage of the population was 41% higher than in the 11 census tracts with the lowest percentage of Black residents. In other words, even for a given level of DUI arrests, there were more roadblocks in census tracts with a higher Black percentage. Additionally the rate of roadblocks per 100 traffic violations (arrests and citations) in the 10 tracts with the highest Black percentage of the population was 40% higher than in the other 11 census tracts.

- More formal statistical analysis supports the conclusions above. Specifically, I use multiple regression analysis in order to control for differences in traffic behavior and socioeconomic factors across census tracts in Madison County (such as frequency of DUI arrests, traffic citations and arrests, vehicle ownership, income, unemployment, and age). When conducting this analysis, I continue to find a statistically significant and positive correlation between the rate of roadblocks and the percentage of the population that is Black. In other words, my analysis incorporates the fact that communities with a higher percentage of Black residents have, on average, other characteristics that are predictive of differences in traffic behavior, such as higher rates of DUI arrests and traffic arrests and citations, lower income, higher unemployment, and younger populations. However, my analysis shows that even after accounting for these factors there remains an unexplained difference in the frequency of roadblocks in communities that have a higher percentage of Black residents relative to communities with a higher percentage of white residents.

3. METHODOLOGY AND DATA

11. In this section, I summarize the methodology I employ in my analysis of the available roadblock data. I first provide a brief overview of factors identified in the record that the MCSD contends it considers when implementing a roadblock. I then offer a description of common statistical methodology used in assessing claims of discrimination, and of how that methodology fits into the broader literature on statistical analysis of differences in policing activity across race. I also provide a detailed summary of the data I rely on in my analysis, and how I use that data to construct relevant control variables included in my regression model.

3.1. The MCSD's stated roadblock policy

12. In analyzing whether roadblocks in Madison County are more frequently placed in Black communities, it is relevant to assess the factors that MCSD contends it considers in placing roadblocks. In documents produced in this case, Defendants have identified factors that they claim are relevant in deciding where to place roadblocks.

13. In their response to the Complaint, Defendants state, "all roadblocks conducted by the Madison County Sheriff's Department are conducted pursuant to the Department's Sobriety Checkpoint Guidelines."[2] Additionally, when asked to "identify all criteria used for selecting locations for roadblocks/checkpoints" by the Plaintiffs, Defendants responded as follows:

> "Some of the criteria used while selecting roadblock/checkpoint locations are traffic complaints, requests by businesses or other entities for safety, and particular intersections where impaired drivers may be expected to travel. Another criteria is that the roadblocks/checkpoints

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[2] Answer and Affirmative Defenses of Defendants, Madison County, Mississippi and Sheriff Randall C. Tucker, In His Official Capacity, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on Behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities*, CIVIL ACTION NO. 3:17-cv-347 WHB LRA, dated June 29, 2017 ("Defendants' Response to the Complaint"), ¶ 140.

locations be spread throughout Madison County and not concentrated in certain areas. No formal system of weighting or priority is used."[3]

14. Defendants thus contend that DUI frequency and concerns for safety related to traffic activity are relevant considerations for the MCSD in deciding where to place roadblocks. As a result, I incorporate measures of DUI arrests and traffic citations and arrests into my analysis of roadblocks.

3.2. Empirical methodology for assessing claims of discrimination

15. As noted above, my analysis in this report seeks to test whether the frequency of roadblocks in communities with substantial percentages of Black residents differs from the frequency of roadblocks in substantially white communities during the time period for which data is available, controlling for non-race factors that can affect the location of a roadblock. By controlling for such non-race factors, my analysis can help assess whether any differences in roadblock frequency can be explained by differences across communities in factors other than race that are predictive of differences in traffic behavior.

16. My analysis in this report relies on a statistical technique called multiple regression analysis. Multiple regression analysis is a widely accepted and common statistical technique in both academia and litigation.[4] Courts have relied on multiple regression analysis in a variety of discrimination matters. For example, the Federal Judicial Center's *Reference Manual for Scientific Evidence* (a document designed to aid federal judges in assessing scientific evidence)

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[3] Response by Defendants, Madison County, Madison County, Mississippi and Sherriff Randall Tucker, in His official capacity, to Plaintiffs' First Set of Interrogatories, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on Behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities,* CIVIL ACTION NO. 3:17-cv-347 WHB LRA, dated October 20, 2017, ¶ 23.

[4] Rubinfeld, Daniel L., "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence*, 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., 2011, pp. 305–306 ("Multiple regression analysis is a statistical tool used to understand the relationship between or among two or more variables…. Over the past several decades, the use of multiple regression analysis in court has grown widely."); Greene, William H., *Econometric Analysis*, 6th Edition, Pearson Prentice Hall, 2008, pp. 8–10 ("The linear regression model is the single most useful tool in the econometrician's toolkit. … The multiple linear regression model is used to study the relationship between a dependent variable and one or more independent variables. … One of the most useful aspects of the multiple regression model is its ability to identify the independent effects of a set of variables on a dependent variable.").

dedicates an entire chapter to multiple regression analysis, including applications to questions of discrimination.[5]

17. Regression analysis is a useful tool to assess claims of discrimination because it allows a researcher to control for relevant factors in the available data that affect the outcome of interest in order to more reliably isolate the effect of the variable on which there is alleged discrimination (e.g., race, gender, age). A large body of academic literature exploring concerns of potential discrimination in labor markets details these methods.[6] The *Reference Manual on Scientific Evidence* describes the importance of controlling for other factors as follows:

> "A correlation between two variables does not imply that one event causes the second. Therefore, in making causal inferences, it is important to avoid spurious correlation. Spurious correlation arises when two variables are closely related but bear no causal relationship because they are both caused by a third, unexamined variable. For example, there might be a negative correlation between the age of certain skilled employees of a computer company and their salaries. One should not conclude from this correlation that the employer has necessarily discriminated against the employees on the basis of their age. A third, unexamined variable, such as the level of the employees' technological skills, could explain differences in productivity and, consequently, differences in salary."[7]

18. There is also a body of research literature focused on the specific question of differential policing and policing outcomes across race. That literature also emphasizes the importance of controlling for relevant, non-race factors when

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[5] Rubinfeld, Daniel L., "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence*, 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., 2011, pp. 305–307 ("Regression analysis has been used most frequently in cases of sex and race discrimination, antitrust violations, and cases involving class certification.").

[6] See, for example, Altonji, Joseph G., and Rebecca M. Blank, "Race and Gender in the Labor Market," Ashenfelter, Orley David C., Card, (Eds.), *Handbook of Labor Economics,* 3, 1999; Blau, Francine D., and Lawrence M. Kahn, "Gender Differences in Pay," *The Journal of Economic Perspectives*, 14(4), 2000, pp. 75–99; Bertrand, Marianne, "New Perspectives on Gender," *Handbook of Labor Economics*, 4b, 2010.

[7] Rubinfeld, Daniel L., "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence,* 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., 2011, p. 309.

assessing claims of racial profiling or bias by police. For example, one study funded by the U.S. Department of Justice to help law enforcement officials and researchers better understand how to analyze data on race and vehicle stops[8] notes "the strongest research methodologies will address the alternative hypothesis that racial/ethnic groups are not equivalent in the nature and extent of their traffic law-violating behavior."[9]

19. Another paper, which summarizes common statistical methods used for analyzing policing data, discusses the importance of controlling for "driving behavior that may be important sources for police decision-making, such as the likelihood of speeding, weaving through traffic, and driving slower than usual,"[10] when analyzing traffic violations across race.

20. As I explain in Section 3.3 below, I am able to account for such concerns in my analysis in this report because I have access to detailed data that tracks each individual traffic arrest and citation by location within Madison County. Using such information, I can construct control variables that measure the frequency of DUI arrests and other traffic violations (arrests and citations) in order to assess how such violations vary across geographic areas with large differences in the percentage of Black residents.

3.3. Summary of available data and control variables for analysis

21. I rely on a set of different data sources produced in this case that track roadblocks and traffic violations in Madison County, as well as publicly available U.S. Census data. Below is a detailed summary of the data sources analyzed, and how I use the data sources to develop the key inputs into my empirical analysis.

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[8] Fridell, Lorie, "By The Numbers: A Guide for Analyzing Race Data from Vehicle Stops," Police Executive Research Forum, 2004, p. ix ("*By the Numbers* is a detailed 'how to' guide for analyzing race data from vehicle stops. It provides a social science framework for understanding the challenges of trying to measure racial bias in policing and presents an array of methods for law enforcement professionals, researchers and other stakeholders to consider when interpreting the vehicle-stop data.")

[9] Fridell, Lorie, "By The Numbers: A Guide for Analyzing Race Data from Vehicle Stops," Police Executive Research Forum, 2004, p. 22.

[10] Ridgeway, Greg, and John MacDonald, "Methods for Assessing Racially Biased Policing," *Race, Ethnicity, and Policing: New and Essential Readings, Infrastructure, Safety, and Environment*, NYU Press, 2010, p. 5.

3.3.1. Data on the date and location of roadblocks

22. Data on the dates and addresses of roadblocks set up by MCSD from January 1, 2012–December 20, 2017 come from three sources of data produced in this litigation by Defendants: computer-aided dispatch ("CAD") records, a handwritten list of roadblocks conducted by the MCSD, and incident reports.

- The CAD roadblock data are the subset of all dispatch data where the "Description" field contains the value "Road Block" ("CAD Roadblocks"). These data provide incident number, date, address, and city fields for each roadblock.[11] I use these data as the primary source of roadblocks.

- I also run a sensitivity analysis that incorporates roadblocks reflected on a handwritten list of dates, start times, end times, and locations that I understand to be roadblocks ("Handwritten Roadblocks") that was produced by Defendants.[12] I have been informed by Counsel that these roadblocks were set up as part of a state program to monitor for DUI incidents. As I discuss below, the Handwritten Roadblocks are incorporated as additional data points in sensitivities of my main results to the extent they do not appear in the list of CAD Roadblocks.

- For a second sensitivity analysis, roadblock data are also imputed from a manual review of incident reports for arrests made at roadblocks that I understand has been undertaken by Counsel for the Plaintiffs ("Additional Roadblocks"). The incident reports provide name, race, date, time, location, and deputy information for these arrests.[13] The dates and locations of Additional Roadblocks do not appear in either the list of CAD Roadblocks or the list of Handwritten Roadblocks.

[11] "Master CAD Report – To Be Produced.csv"

[12] "Roadblock Locations (Handwritten).xlsx"

[13] "Unlisted Roadblocks.xlsx"

- CAD Roadblocks account for 81.6% of the roadblock observations in the three data sources I analyze.

23. The data from these three sources are combined into a single dataset including date and address fields. Each roadblock is assigned to a census tract in Madison County based on its geographic coordinates.[14] I then define a unique roadblock as a roadblock in a given location on a given day, and then count the total roadblocks by year at the census tract level in order to create a dataset of the frequency of roadblocks at the census tract level by year for the years 2012–2017. I calculate this sum four ways: (1) with only CAD Roadblocks, (2) with CAD Roadblocks plus Handwritten Roadblocks, (3) with CAD Roadblocks plus Additional Roadblocks, and (4) with roadblocks from all three sources. The number of roadblocks per capita is then calculated for each of these approaches by dividing the total number of roadblocks in a given census tract and year by the population of the census tract.

3.3.2. Data on traffic violations by location

24. As discussed above, it is important to include control variables in my analysis that can directly measure differences in the underlying traffic behavior between different communities in Madison County for two reasons: (1) the research literature assessing the role of race in traffic stops emphasizes the importance of controlling for differential traffic behavior; and (2) the MCSD indicates that DUIs and traffic safety are factors in implementing roadblocks.

25. I understand that the CAD data produced by the Defendants includes all incidents in which MCSD officers are involved that are called into central dispatch, not only those relating to roadblocks.[15] As a result, these data may be

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[14] I convert the addresses into longitude and latitude coordinates. Only roadblocks for which an accurate set of coordinates can be determined are used in my analysis. This removes 14.9% of the roadblocks listed in the three data sources from my analysis.

[15] Defendants' Memorandum of Authorities in Opposition to Plaintiffs' Motion to Compel, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on behalf of a class of all other similarly situated, v. Madison County, Mississippi; Sheriff Randall C. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities*, CIVIL ACTION NO. 3:17-cv-347 WHB LRA, dated November 3, 2017 ("Memorandum of Authorities") broadly describes the contents of the CAD database. Defendants have represented that the CAD data include information on roadblocks, traffic stops, and other law enforcement encounters. Defendants have also represented that "[w]henever an incident is brought to the attention of a dispatcher in the Sheriff's Department, that information goes into the CAD database and is assigned an incident number." Memorandum of Authorities, p. 2.

used to construct control variables such as those described above. These data cover the period from January 1, 2012–December 20, 2017. They include date and address fields; times for when dispatch received a call regarding an incident; when an officer was dispatched; when an officer arrived and when a stop was cleared; a field containing a code signifying how the incident was resolved (e.g., in arrest, citation, etc.); and a field indicating the type of violation. These data do not include race information.

26. In order to include control variables for traffic behavior, I construct two variables from the CAD data. One accounts for the prevalence of DUI arrests per census tract,[16] and the other accounts for the prevalence of traffic violations per census tract, including arrests and citations issued.[17]

3.3.3. Race and socioeconomic information by census tract

27. The U.S. Census Bureau ("Census Bureau") provides detailed annual data at *the census tract level* for key demographic and socioeconomic factors in my analysis, including race, population, income, employment, age, and vehicle ownership. I collect data from the Census Bureau's five year estimates from 2012–2016, in order to construct year-by-year measures of the variables described above.[18] These data allow me to incorporate detailed information for each of the 21 census tracts in Madison County into my analysis.

28. I conduct my analysis at the census tract level for a few reasons. First, race data is not available for each individual police interaction in the CAD data, thus I cannot determine the race of the individuals stopped for any specific stop associated with a roadblock. Census tract data from the Census Bureau, on the other hand, does have race information.

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[16] Incidents included in DUI arrests are those in the CAD data that: 1) have a value for the variable "DISPO" of "ARREST MADE"; and 2) have a value for the variable "DESCRIPTION" of "INTOXICATED DRIVER (D.U.I.)".

[17] Incidents included in traffic arrests and citations are those in the CAD data that: 1) have a value for the variable "DISPO" of "ARREST MADE" or "CITATION ISSUED"; and 2) have a value for the variable "DESCRIPTION" of "INTOXICATED DRIVER (D.U.I.)", "TRAFFIC STOP (V.T.O.)", "STOPPING SUSPICIOUS VEHICLE", "TRAFFIC OFFENSES", "TRAFFIC-RECKLESS DRIVING", "TRAFFIC-CARELESS DRIVING", "TRAFFIC-DRAG RACING", "TRAFFIC-OBSTRUCTING TRAFFIC", "TRAFFIC-PASSING SCHOOL BUS", or "TRAFFIC-OTHER TRAFFIC VIOLATIO".

[18] The estimate for each year is based on the preceding five years of data from the American Community Survey (ACS). For example, the estimate for 2012 is based on the ACS population estimates from 2008–2012. The five year estimate including 2017 has not yet been released, so I use the most recent five year estimate (2012–2016) for the census data in both 2016 and 2017.

29. Second, data on the traffic behavior of each individual citizen are not available. Therefore, it is not possible to perform an analysis that controls for traffic behavior at the individual level with the available data. On the other hand, using the crime data produced by the MCSD and available socioeconomic variables from the Census Bureau, I can construct measures of traffic behavior for each census tract.

30. Finally, because roadblocks are policing actions that should affect all motorists passing through a specific geographic area (rather than targeting a specific person), it is reasonable to analyze the placement of roadblocks within refined geographic sub-areas (like census tracts).

31. It is important to note that census tracts are a relatively fine categorization of geographic area. For example, there are 73,057 census tracts in the U.S., 664 in Mississippi and 21 in Madison County alone.[19] This relatively fine categorization of geography is important for my analysis because it allows me to analyze how the frequency of roadblocks changes across numerous geographic sub-areas of Madison County that have substantially different racial breakdowns.

32. For example, Exhibit 1 shows the percentage of the population that is Black in each of the 21 census tracts in Madison County over the period 2012–2017. As is clear, there is large variation across the tracts with respect to the percentage of population that is Black—ranging from less than 11% to almost 90%.

[19] "2010 Census – Census Tract Reference Map: Madison County, MS," available at *U.S. Census Bureau*, https://www2.census.gov/geo/maps/dc10map/tract/st28_ms/c28089_madison/DC10CT_C28089_001.pdf; "2010 Census Tallies of Census Tracts, Block Groups & Blocks," available at *U.S. Census Bureau*, https://www.census.gov/geo/maps-data/data/tallies/tractblock.html.

Exhibit 1

Average Percentage of the Population That is Black by Census Tract within Madison County (2012–2017)

Census Tract	Average Black Population Percentage
28089030101	10.7%
28089030202	10.9%
28089030203	11.6%
28089030301	11.6%
28089030206	13.0%
28089030204	14.7%
28089030104	16.5%
28089030205	17.9%
28089030107	18.0%
28089030201	18.6%
28089030400	28.0%
Average of Census Tracts with Low Black Population Percentage	17.6%
28089030105	46.2%
28089030106	47.6%
28089030302	49.3%
28089030700	58.4%
28089030800	59.6%
28089030108	65.6%
28089030900	69.5%
28089030600	83.7%
28089031000	84.0%
28089030500	89.5%
Average of Census Tracts with High Black Population Percentage	66.0%

Source: American Community Survey Five Year Estimates, U.S. Census Bureau

33. It is notable that the 21 census tracts are divided cleanly into two groups. Of the 21 census tracts, 11 have a relatively low percentage of Black residents (28% or lower), while 10 have a relatively high percentage of Black residents (46% or higher). On average, the percentage of Black residents in the first set of tracts is 17.6%, while it is 66.0% in the second set. This large variation in the percentage of the population that is Black across census tracts is central to my research

design because it allows me to examine how the frequency of roadblocks (and other factors related to roadblocks) differs across areas with large differences in the Black population.[20]

34. As noted above, in addition to race, I also collect data from the Census Bureau on relevant socioeconomic and demographic variables, including population, median income, unemployment rate, percentage of population age 15–24, and vehicle ownership for each census tract. In Section 3 below, I include these variables in my regression model because they can help account for differences in relevant behavior that might not be fully accounted for by the direct measures of traffic behavior in the MCSD data. For example, vehicle ownership is a predictor of how frequently people drive. Age is also understood to be a direct correlate of traffic behavior—research indicates that younger drivers drive more recklessly on average.[21] Income and unemployment are indicators for general economic well-being, which are associated with DUIs and levels of crime.[22] As I discuss more below, income and unemployment can also serve as controls for the MCSD's allocation of policing resources. As a result, disparities among these indicators across census tracts also provide potential explanations for differences in the rates of roadblocks across census tracts.

[20] Without large differences in race across geographic areas, we would not be able to compare differences in predominately Black communities and predominantly white communities. The variation across census tracts in Madison County allows for such comparisons. This type of research design, in which a single variable cleanly delineates two groups of people with and without a characteristic of interest, is a widely used research design in economic research that allows for quantification of the effect of that characteristic on relevant outcomes. See, for example, Angrist, Joshua, and Jörn-Steffen Pischke, "Undergraduate Econometrics Instruction: Through Our Classes, Darkly," *Journal of Economic Perspectives,* 31(2), 2017, pp. 125–144.

[21] Fridell, Lorie, "By The Numbers: A Guide for Analyzing Race Data from Vehicle Stops," Police Executive Research Forum, 2004, pp. 19–22.

[22] Chalfin, Aaron, and Justin McCrary, "Criminal Deterrence: A Review of the Literature*," Journal of Economic Literature*, 55(1), 2017, pp 5–48; Impinen, Antti et al., "The Association between Social Determinants and Drunken Driving: A 15-Year Register-based Study of 81,125 Suspect," *Alcohol and Alcoholism*, 46(6), 2011, pp. 721–728; Perrine, M.W., Raymond C. Peck, and James C. Fell, "Epidemiologic Perspectives on Drunk Driving," *Surgeon General's Workshop on Drunk Driving, Background Papers*, U.S. Department of Health and Human Services, 1988, pp. 35–76.

4. ANALYSIS OF THE LOCATION AND FREQUENCY OF ROADBLOCKS

35. In this section, I present the findings of my analysis of roadblocks. I start my analysis in Section 4.1 with a set of descriptive analyses that highlight the general patterns in the location and frequency of roadblocks across the 21 different census tracts in Madison County. I show that the frequency of roadblocks is generally higher in census tracts with a substantially higher percentage of Black residents.

36. In Section 4.2, I then present the findings of my regression analysis, where I formally test whether the frequency of roadblocks is higher in census tracts with a higher percentage of Black residents, controlling for other factors that are predictive of differences in traffic behavior. I find that, even after controlling for these factors, roadblocks are more frequent in census tracts with a higher percentage of the population that is Black.

4.1. Patterns of roadblocks across census tracts

37. As discussed above in Section 3, an important fact about Madison County is that the percentage of the population that is Black varies substantially across the 21 census tracts inside the county. This fact about Madison County allows me to examine whether the frequency of roadblocks is higher in areas within Madison County that have a substantially higher percentage of Black residents.

38. Exhibit 2 presents a map of the locations of the roadblocks in Madison County during the period 2012–2017, as well as the percentage of the population that is Black in each census tract. In total, there were 2,004 roadblocks established during this time period,[23] with at least one roadblock in each of the 21 different census tracts—ranging from as few as 7 in one census tract[24] to 275 in one of the census tracts in Canton in the center of the map.[25] Thus, the general geographic scope of the roadblocks extended to most areas of the county.

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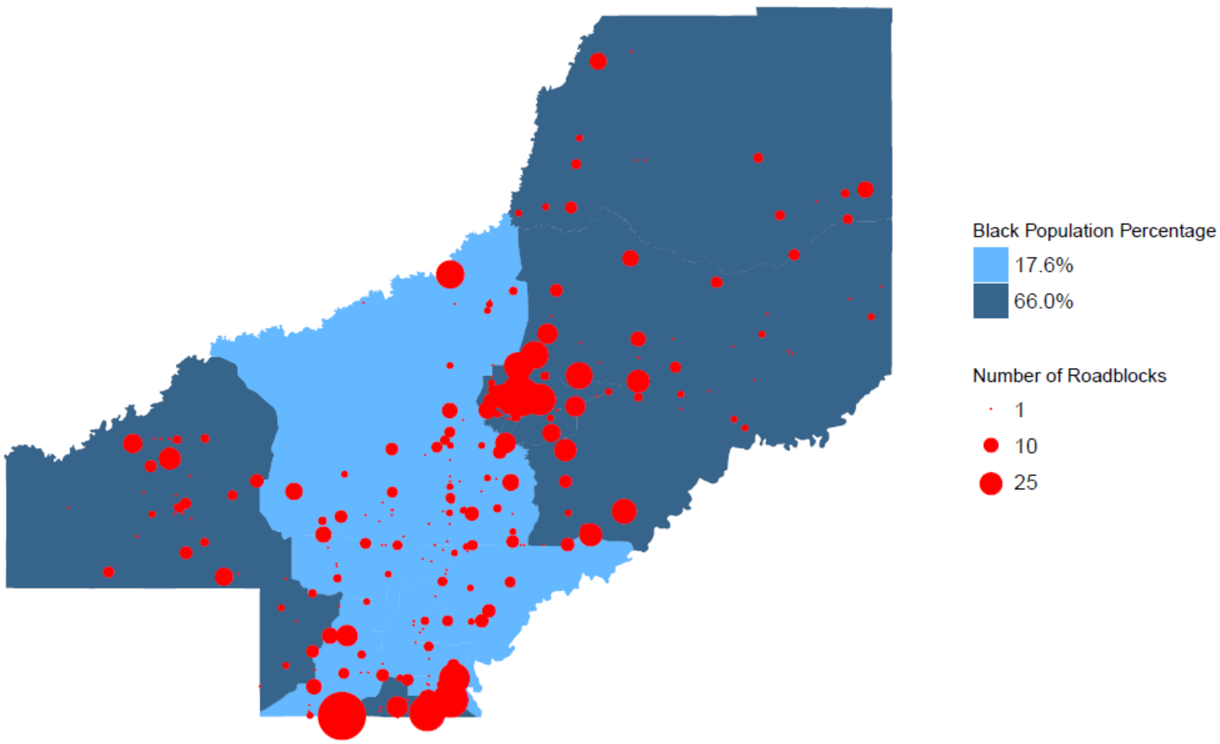
[23] These 2,004 unique roadblocks are composed of 1,697 CAD Roadblocks, 161 Handwritten Roadblocks, and 146 Additional Roadblocks, after removing duplicates based on date and location.

[24] Census tract 28089030202.

[25] Census tract 28089030600.

Exhibit 2

Location of Roadblocks by Census Tract within Madison County (2012–2017)



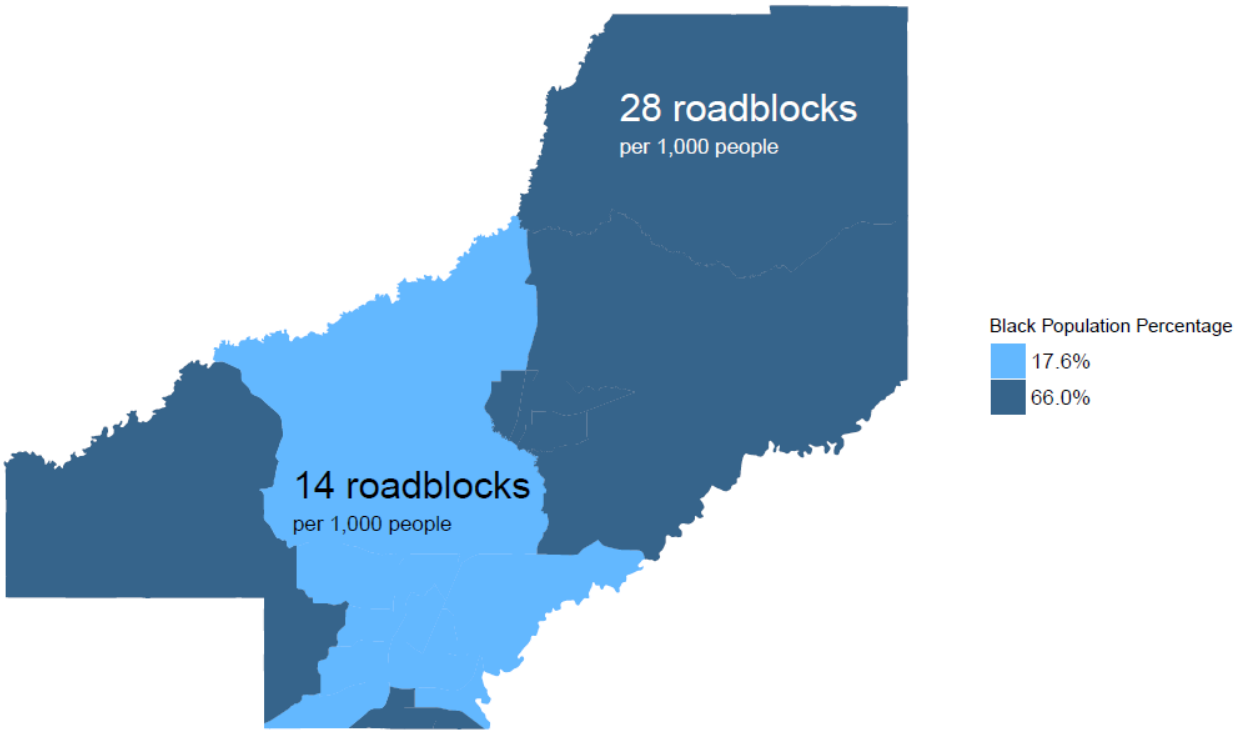
Source: American Community Survey Five Year Estimates, U.S. Census Bureau; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; Master CAD Report – To Be Produced.csv

39. One thing that Exhibit 2 does not capture is the population of different census tracts. In Exhibit 3, I report the average number of roadblocks *per 1,000 citizens* for the 11 census tracts with the lowest percentage of Black residents (with an average of 17.6%) compared to the 10 census tracts with the highest percentage of Black residents (with an average of 66.0%). As seen in the exhibit, the number of roadblocks per 1,000 citizens in census tracts with a relatively low percentage of Black residents is 14, while for census tracts with a relatively high percentage of Black residents it is 28.[26] That is, the frequency of roadblocks is twice as high in census tracts with a relatively high percentage of Black residents as it is in census tracts with a relatively low percentage of Black residents.

[26] Total Population figures are from the 2012–2016 ACS Five Year Estimates. The Total Population for each group of census tracts is a weighted average across 2012 to 2017. Note that 2016 data is duplicated for 2017 because the 2017 ACS estimates have not yet been released.

Exhibit 3

Frequency of Roadblocks by Racial Breakdown



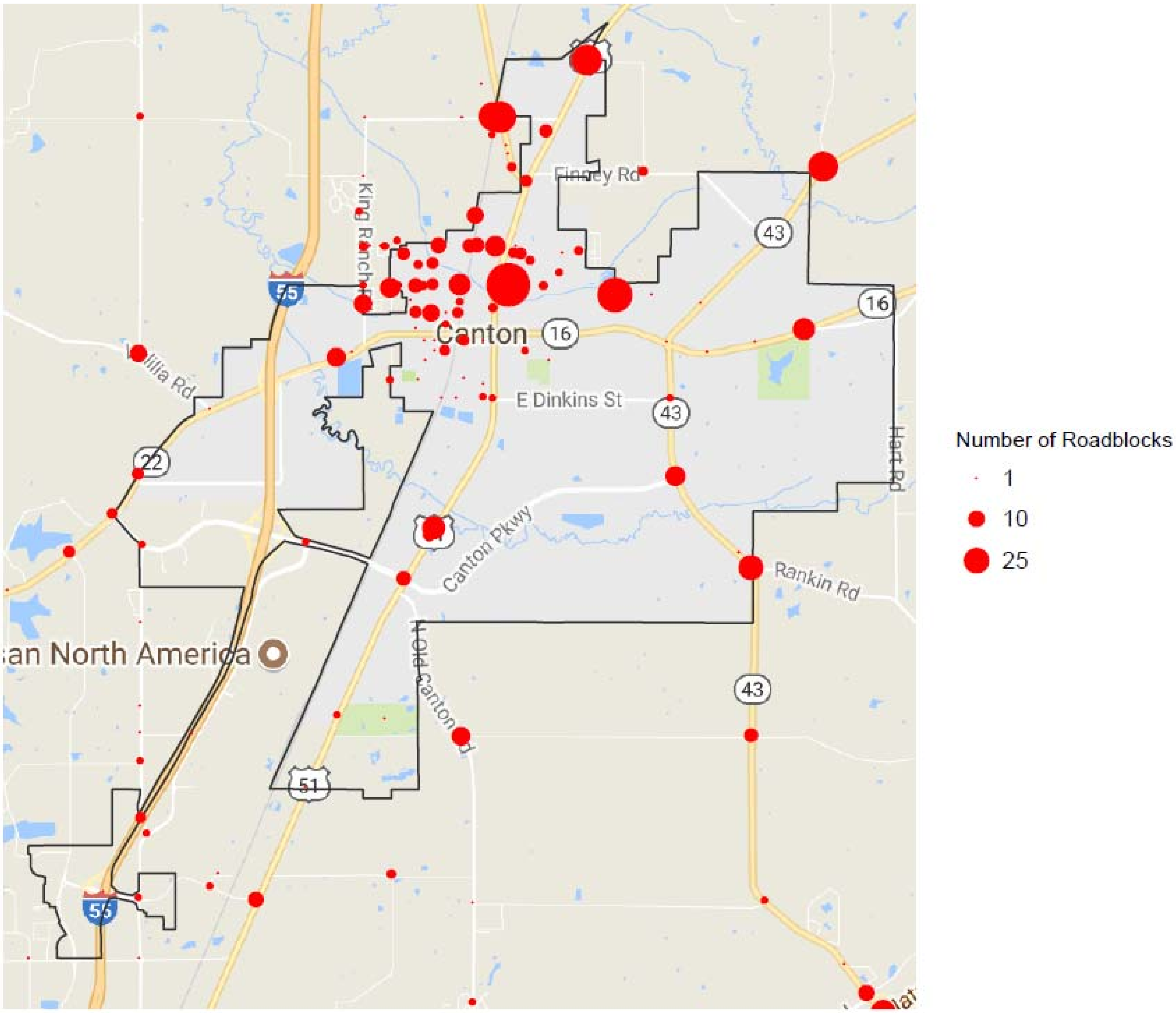
Source: Master CAD Report – To Be Produced.csv; Roadblock Locations(Handwritten).xlsx; Unlisted Roadblocks.xlsx; American Community Survey (ACS) Five Year Estimates, U.S. Census Bureau

40. Exhibit 4 presents a map that zooms in on Canton, a city that is approximately 70.8% Black, according to the American Community Survey Five Year Estimate from 2016.[27] As is clear, the roadblocks are particularly clustered in a relatively small area of Canton towards the north.

[27] American Community Survey Five Year Estimates for All Places in Madison County, Mississippi, Demographic and Housing Estimates, 2016.

Exhibit 4

Roadblocks Located in Canton



Source: American Community Survey Five Year Estimates, U.S. Census Bureau; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; Master CAD Report – To Be Produced.csv; Google Maps

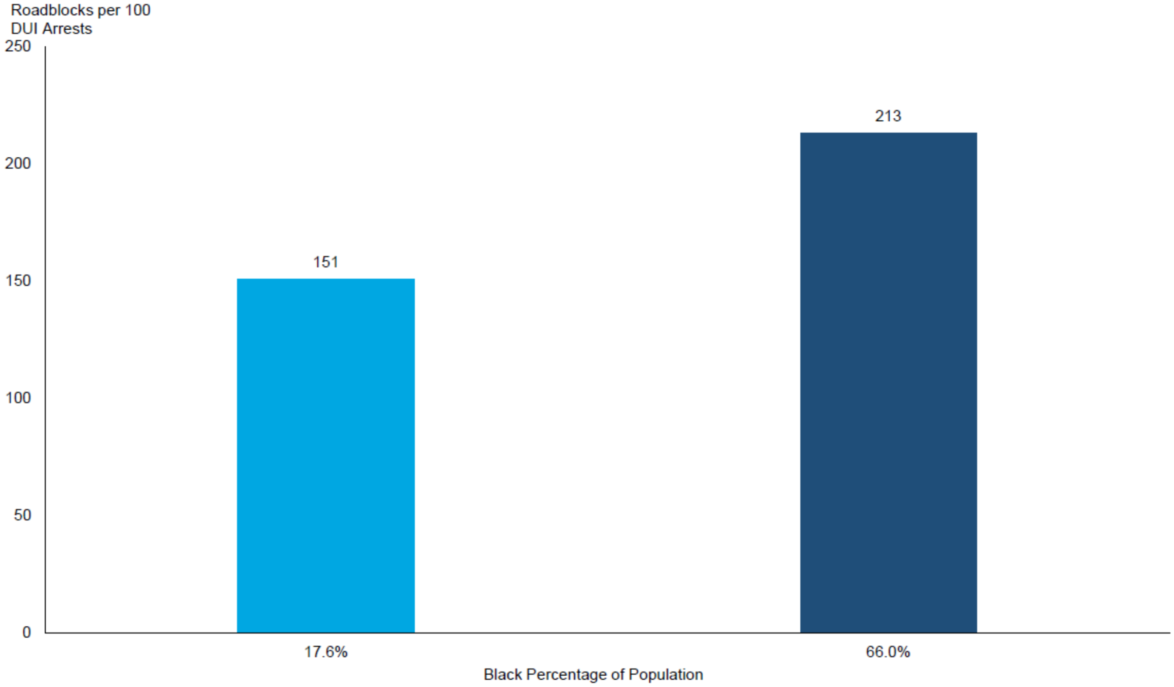
41. An important question is whether the higher rate of roadblocks in the different areas of Madison County might simply reflect different rates of unsafe traffic behavior. More roadblocks would be expected in some areas if there were higher rates of unsafe traffic behavior in those areas. Exhibit 5 presents two ways to think about that question. First, it presents the number of roadblocks *per* 100 DUI arrests for the 11 census tracts with the lowest percentage of Black residents (with an average of 17.6%) compared to the 10 census tracts with the highest

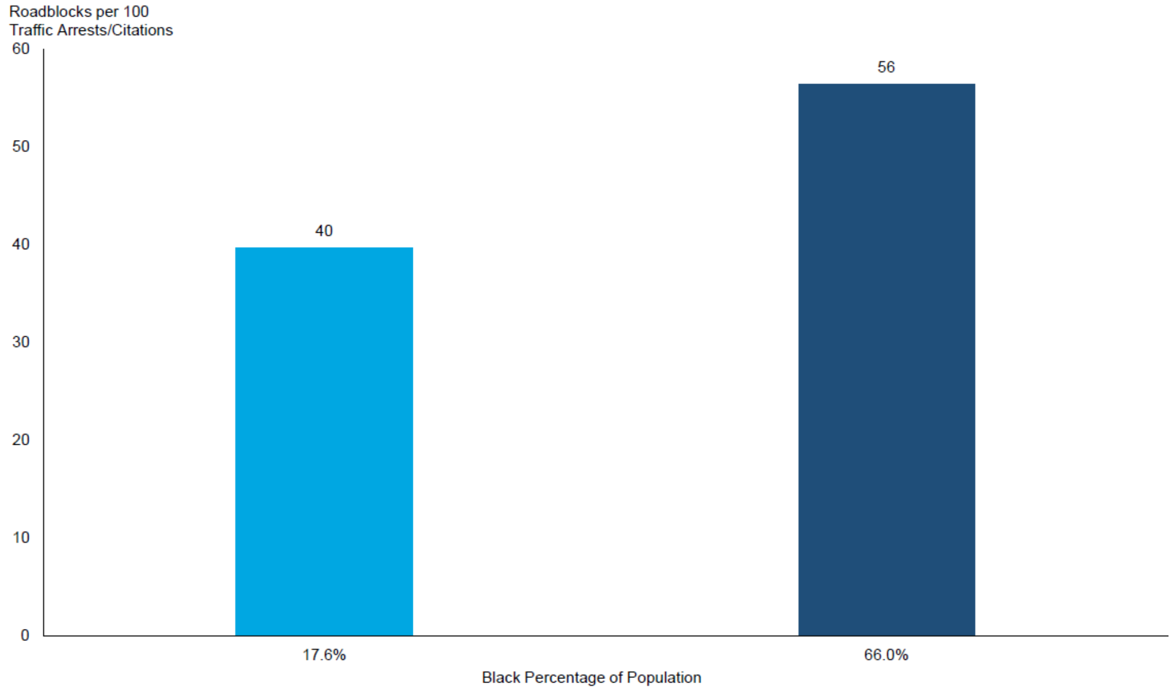
percentage of Black residents (with an average of 66.0%). As seen in the exhibit the number of roadblocks per 100 DUI arrests in census tracts with a relatively low percentage of Black residents is 151, while for census tracts with a relatively high percentage of Black residents it is 213, which is 41% higher.

42. Second, Exhibit 5 also presents the number of roadblocks *per* 100 traffic arrests and citations in the same two sets of census tracts. As seen in the exhibit, the number of roadblocks per 100 traffic arrests and citations in census tracts with a relatively low percentage of Black residents is 40, while for census tracts with a relatively high percentage of Black residents it is 56, which is 40% higher.

Exhibit 5

Roadblocks per 100 DUI and Traffic Violations by Racial Breakdown





Source: Master CAD Report - To Be Produced.csv; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; American Community Survey Five Year Estimates, U.S. Census Bureau

43. In sum, the data indicate that: (a) roadblocks are more likely to be placed in census tracts with a higher percentage of Black residents, (b) roadblocks are sometimes clustered in large numbers in certain neighborhoods, and (c) the relatively higher frequency of roadblocks cannot be explained by a relatively higher number of DUI arrests or traffic arrests and citations.

4.2. Regression analysis

44. I now turn to my regression analysis, which uses multiple control variables to analyze the different frequency of roadblocks across census tracts. As detailed above in Section 3, regression analysis is a widely accepted method in both academic research and in litigation to analyze the effect of one variable (in this case, race) on another (in this case, frequency of roadblocks), while controlling for a set of control variables that also affect the variable of interest (frequency of roadblocks). In the current matter, I use regression analysis to better understand whether the relationship observed between the Black percentage of the population in Madison County and roadblocks across census tracts (discussed in Section 4.1 above) can be explained by differences between the census tracts in factors other than race that are predictive of differences in traffic behavior.

45. As discussed in Section 3 above, I include the following control variables in my regression model. The first four variables help control for differences in traffic behavior across the 21 census tracts, while the final two variables help control for economic status, which is correlated with DUIs, general crime/safety, and the allocation of police resources. The control variables I include are:

- DUI arrests per 1,000 people;
- Traffic arrests and citations per 1,000 people;
- Percentage of households with at least one vehicle;
- Percentage of population between ages 15-24;
- Median household income; and
- Unemployment rate.

46. Exhibit 6 presents the results of my regression analysis based on the CAD Roadblocks. It shows three different regressions. The first regression controls for DUI arrests and other factors from the census data, the second controls instead for traffic arrests and citations with other factors from the census data, and the third controls for both DUI arrests and traffic violations (arrests and citations) with

other factors from the census data. There are a few important things to note about the results.

- First, the effect of the percentage of Black residents is statistically significant and positive at less than the 5% level in all three models, which is the standard level of significance used in most academic research and in litigation.[28] These results indicate that, even after controlling for variables that are predictive of differences in traffic behavior, roadblocks are statistically significantly more likely to occur in areas with a higher percentage of Black residents.

- Second, DUI arrests are a very strong predictor of roadblocks. This can be seen by looking at the R-Squared of the three models. The R-squared is a statistic that tells us how well the control variables in the regression model explain the frequency of roadblocks across the different census tracts.[29] The model with DUI arrests and census variables as control variables has an R-squared of 0.646. What this means is that level of DUI arrests per 1,000 people in a given census tract explains 64.6% of the variation in roadblocks across census tracts, together with demographic controls. That is a relatively large R-squared,[30] and provides direct evidence that the model has significant explanatory power for roadblocks. The model with traffic arrests and citations and census variables, on the other hand, has an R-squared of less than half of the model with DUI arrests and census controls (0.293), which means that traffic arrests and citations with census controls explain roadblock frequency less than half as well as DUI arrests and census controls.

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[28] Kaye, David H., and David A. Freedman, "Reference Guide on Statistics," *Reference Manual on Scientific Evidence*, 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., p. 251; Rubinfeld, Daniel L., "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence*, 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., 2011, pp. 320–321.

[29] Rubinfeld, Daniel L., "Reference Guide on Multiple Regression," *Reference Manual on Scientific Evidence*, 3rd Edition, Federal Judicial Center, The National Academies Press, Washington, D.C., 2011, p. 316 ("In general, the more complete the explained relationship between the included explanatory variables and the dependent variable, the more precise the results.").

[30] Greene, William H., *Econometric Analysis,* 6th Edition, Pearson Prentice Hall, 2008, p. 38.

Given this fact, the models with DUI arrests as a control are my preferred models.

- Third, the size of the coefficient on the percentage of Black residents (0.062) in my fullest model (the third column—including both DUI arrests and traffic arrests and citations as controls) is substantial. The following example helps explain what the coefficient signifies. Suppose that we compare an area that was 20% Black to one that was 80% Black. The coefficient means that there would be 3.73 more roadblocks per 1,000 citizens on average in the area that was 80% Black.[31] To put that into context, the average census tract in Madison County had about 5,000 people per year during the relevant period. For such an average census tract, if the percentage of Black residents is 80% instead of 20%, my model predicts that there will be over 18 more roadblocks per year (3.73 more roadblocks per 1,000 people is 18.65 total roadblocks), or about 112 more roadblocks in total over the 6 years of data I analyze.

[31] The effect of moving from an area that was 20% Black to one that was 80% Black in my model is equal to (80-20)*0.06218, which equals 3.7308.

Exhibit 6

Regression Results: Effect of Race on Frequency of Roadblocks, Controlling for Other Factors (2012–2017)

Variable	(1) With DUI Arrests	(2) With Traffic Citations/Arrests	(3) With DUI Arrests and Traffic Citations/Arrests
Black Percentage of Population	0.06492	0.05829	0.06218
standard error	0.01756	0.02486	0.01721
p-value	0.00033	0.02073	0.00044
Number of DUI Arrests Per 1,000 People	1.22070		1.38900
standard error	0.10390		0.12150
p-value	0.00000		0.00000
Number of Traffic Citations/Arrests Per 1,000 People		0.15220	-0.10300
standard error		0.04928	0.04075
p-value		0.00251	0.01281
Median Household Income (in Thousands)	0.03166	0.01685	0.02669
standard error	0.01588	0.02260	0.01566
p-value	0.04851	0.45750	0.09094
Unemployment Rate	-0.11910	-0.36860	-0.07771
standard error	0.07720	0.10540	0.07727
p-value	0.12550	0.00066	0.31660
Percentage of Households with At Least One Vehicle	-0.05640	-0.33580	-0.09574
standard error	0.07273	0.10080	0.07282
p-value	0.43960	0.00115	0.19120
Percentage of Population between Ages 15-24	-0.03368	-0.08256	-0.04544
standard error	0.04824	0.06838	0.04742
p-value	0.48640	0.22970	0.33980
Constant	2.58350	33.99400	7.05080
standard error	7.80860	10.80700	7.83940
p-value	0.74130	0.00209	0.37030
Observations	126	126	126
Adjusted R-Squared	0.646	0.293	0.662

Source: Master CAD Report - To Be Produced.csv; American Community Survey Five Year Estimates, U.S. Census Bureau

47. I have also run a set of sensitivity analyses to test whether my results are robust to the inclusion of the two sources of roadblocks outside of the CAD data, Handwritten Roadblocks and Additional Roadblocks. When I run my regression model including roadblocks from each of these two sources, I continue to find a

statistically significant and positive effect of the percentage of the population that is Black on the frequency of roadblocks.[32]

48. I have also confirmed that my results are robust to restricting attention to subsets of the years for which data are available. At the request of Counsel, I specifically test whether my results are robust restricting attention to roadblocks that occurred in 2014 through 2017, and whether they are robust to restricting attention to roadblocks that occurred in only 2015 and 2016. I continue to find a statistically significant and positive effect of the percentage of the population that is Black on the number of roadblocks in these specifications.[33]

4.3. A note on the data sample

49. I understand that Defendants contend that the MCSD focuses its policing resources only on the unincorporated areas of Madison County, and, to the extent they police within the incorporated areas, they focus disproportionately in cities that need more resources.[34] The available data on roadblocks are not consistent with this claim, as roadblocks are conducted by the MCSD in incorporated areas of Madison County.

50. Even if the MCSD did focus its policing in lower income areas of Madison County, this would not undermine my regression analysis because my key control variables (DUI arrests and traffic arrests and citations) capture policing activities by the MCSD. Thus, to the extent the MCSD's roadblocks are concentrated in certain lower income areas, my control variables would account for that fact because they also measure the MCSD's policing activities. In other words, if one were concerned that the higher rate of roadblocks in census tracts with a higher percentage of Black residents reflected the fact that the MCSD polices more heavily in those tracts, my model indicates that—even after accounting for the heavier policing activity in those areas—roadblocks are significantly more common in tracts with a higher percentage of Black residents.

[32] See Appendix C.

[33] See Appendix C.

[34] Defendants' Response to the Complaint, ¶ 9.

51. Further, because my model includes controls for income and unemployment, it controls for the possibility that the MCSD's policing intensity varies with the income of a neighborhood.

5. CONCLUSION

52. In sum, available data show that (a) Madison County's 21 census tracts can be divided broadly into two geographic areas with substantially different racial populations—one area which is 17.6% Black and one area which is 66.0% Black, and (b) the frequency of roadblocks per 1,000 residents is higher in the areas of Madison County where a relatively higher percentage of the population is Black.

53. A multivariate regression analysis that controls for differences across each of the 21 census tracts that are predictive of traffic behavior—the rate of DUI arrests, traffic arrests and citations, average income, age, vehicle ownership, unemployment rate—finds a statistically significant and positive relationship between the number of roadblocks per year in census tracts in Madison County and the percentage of the population that is Black in those census tracts. In other words, even after accounting for the fact that census tracts with a higher percentage of Black residents have higher levels of DUI arrests, higher levels of traffic arrests and citations, and different socioeconomic characteristics, there remains an unexplained gap in the rate of roadblocks in those communities.

Bryan Ricchetti, Ph.D.

EXHIBIT 1

Average Percentage of the Population That is Black by Census Tract within Madison County

2012–2017

Census Tract	Average Black Population Percentage
28089030101	10.7%
28089030202	10.9%
28089030203	11.6%
28089030301	11.6%
28089030206	13.0%
28089030204	14.7%
28089030104	16.5%
28089030205	17.9%
28089030107	18.0%
28089030201	18.6%
28089030400	28.0%
Average of Census Tracts with Low Black Population Percentage	17.6%
28089030105	46.2%
28089030106	47.6%
28089030302	49.3%
28089030700	58.4%
28089030800	59.6%
28089030108	65.6%
28089030900	69.5%
28089030600	83.7%
28089031000	84.0%
28089030500	89.5%
Average of Census Tracts with High Black Population Percentage	66.0%

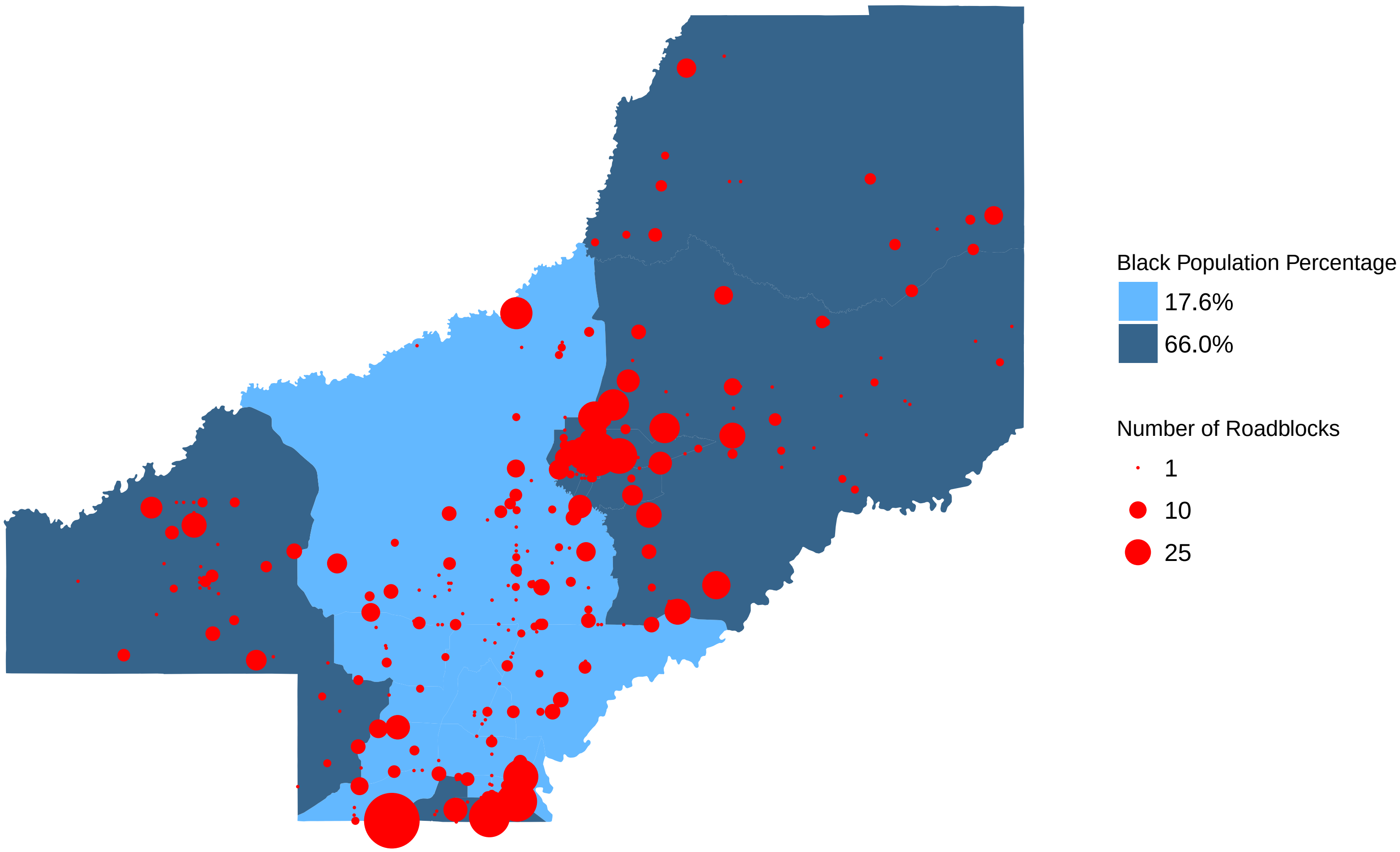
Source: American Community Survey Five Year Estimates, U.S. Census Bureau

Note: Average Black population percentage figures are calculated from the 2012−2016 American Community Survey Five Year Estimates. The Census Bureau has yet to release 2013−2017 American Community Survey Five Year Estimates. Weighted average Black population percentages across 2012−2017 are reported, and 2016 data are used for 2017.

EXHIBIT 2

Location of Roadblocks by Census Tract within Madison County

2012−2017

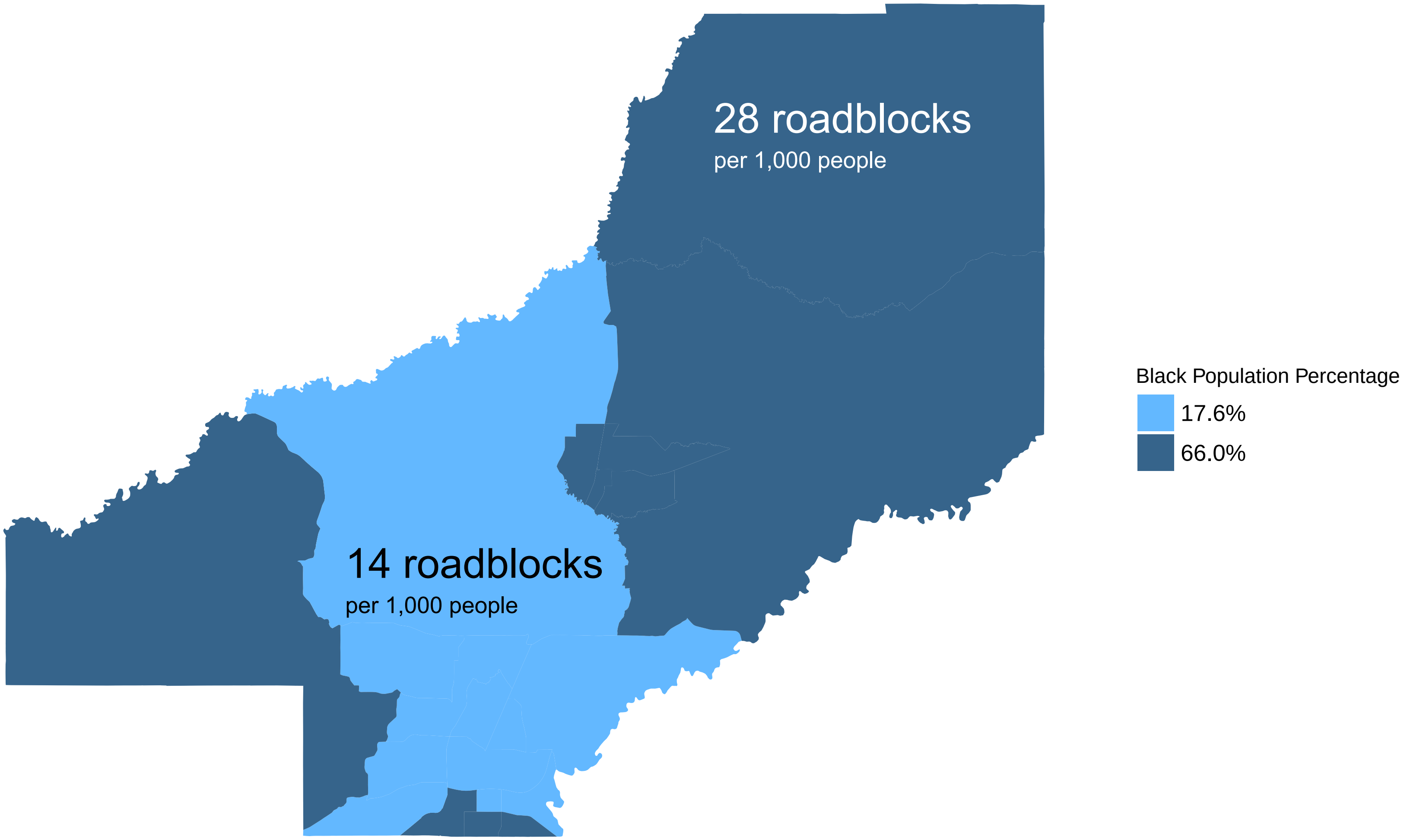


Source: American Community Survey Five Year Estimates − Geodatabase Format, U.S. Census Bureau; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; Master CAD Report − To Be Produced.csv

Note: Census tracts that are 46% Black or more are shaded dark blue, and census tracts that are 28% Black or less are shaded light blue. There are no census tracts with a Black population percentage between 29% and 45%. Black population percentage and total population figures are from the ACS Five Year Estimates. This map uses the weighted average across 2012−2017 for both of these values, and 2016 data is used for 2017. This map includes roadblocks in Madison County for which accurate coordinates are available. Dots are scaled by the number of roadblocks at a given longitude and latitude.

EXHIBIT 3

Frequency of Roadblocks by Racial Breakdown

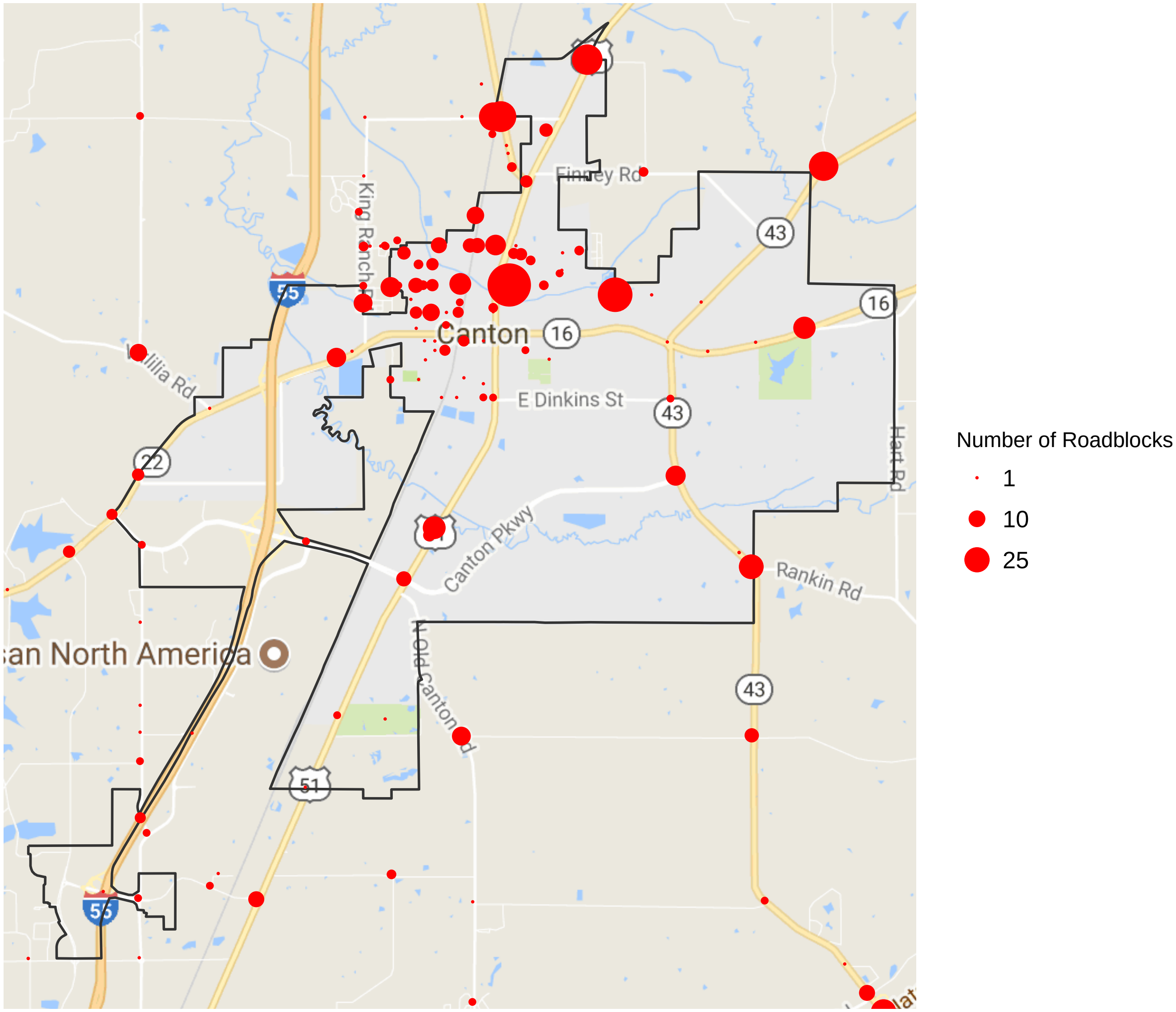


Source: American Community Survey Five Year Estimates − Geodatabase Format, U.S. Census Bureau; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; Master CAD Report − To Be Produced.csv

Note: Census tracts that are 46% Black or more are shaded dark blue, and census tracts that are 28% Black or less are shaded light blue. There are no census tracts with a Black population percentage between 29% and 45%. Black population percentage and total population figures are from the ACS Five Year Estimates. This map uses the weighted average across 2012−2017 for both of these values, and 2016 data is used for 2017. Roadblock counts include roadblocks from 2012 through 2017.

EXHIBIT 4

Roadblocks Located in Canton

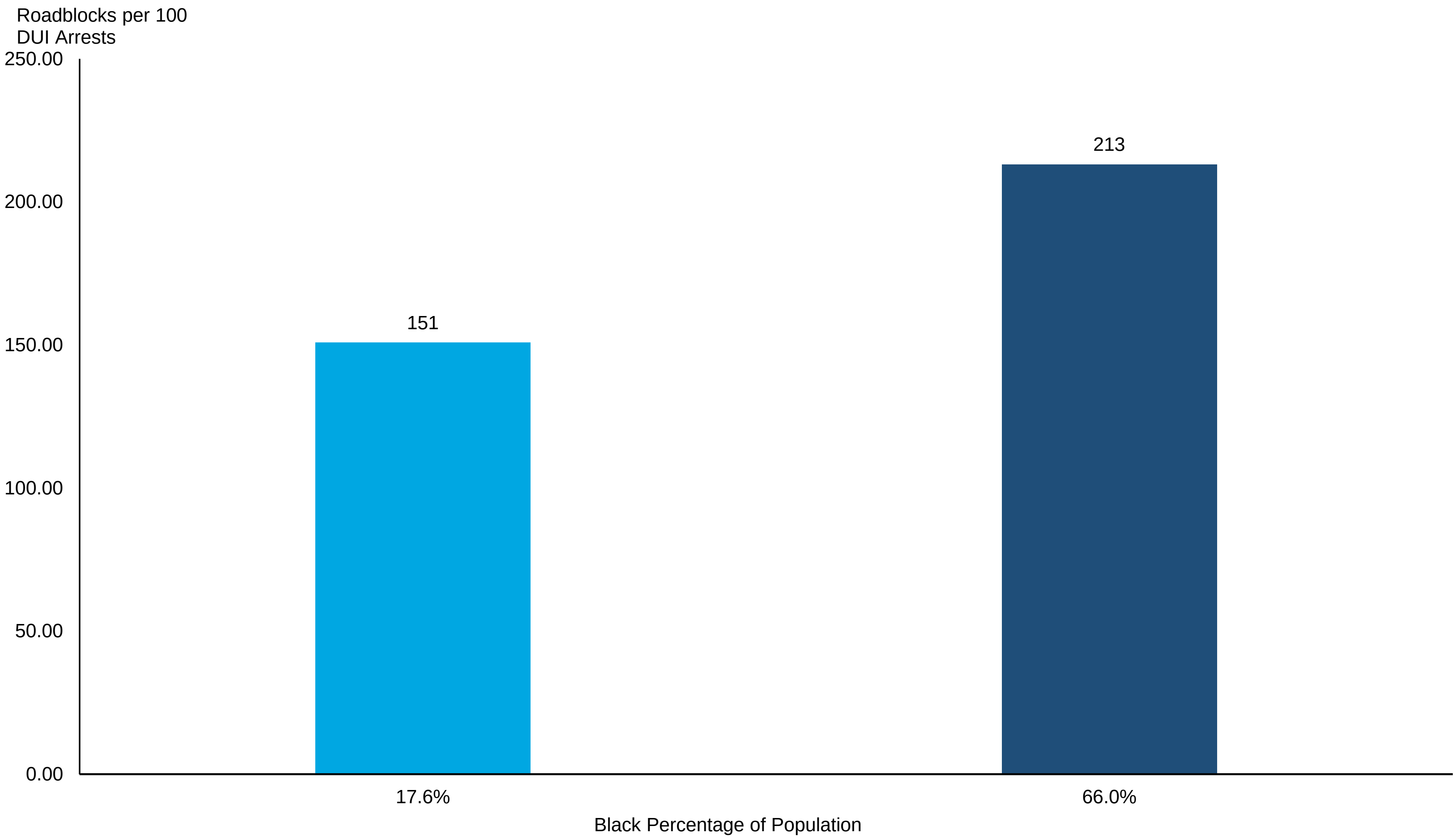


Source: Tiger/Line Shapefiles: Places − Mississippi, U.S. Census Bureau; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; Master CAD Report − To Be Produced.csv; Google Maps

Note: This map includes roadblocks for which accurate coordinates are available. Dots are scaled by the number of roadblocks at a given longitude and latitude.

EXHIBIT 5

Roadblocks per 100 DUI and Traffic Violations by Racial Breakdown

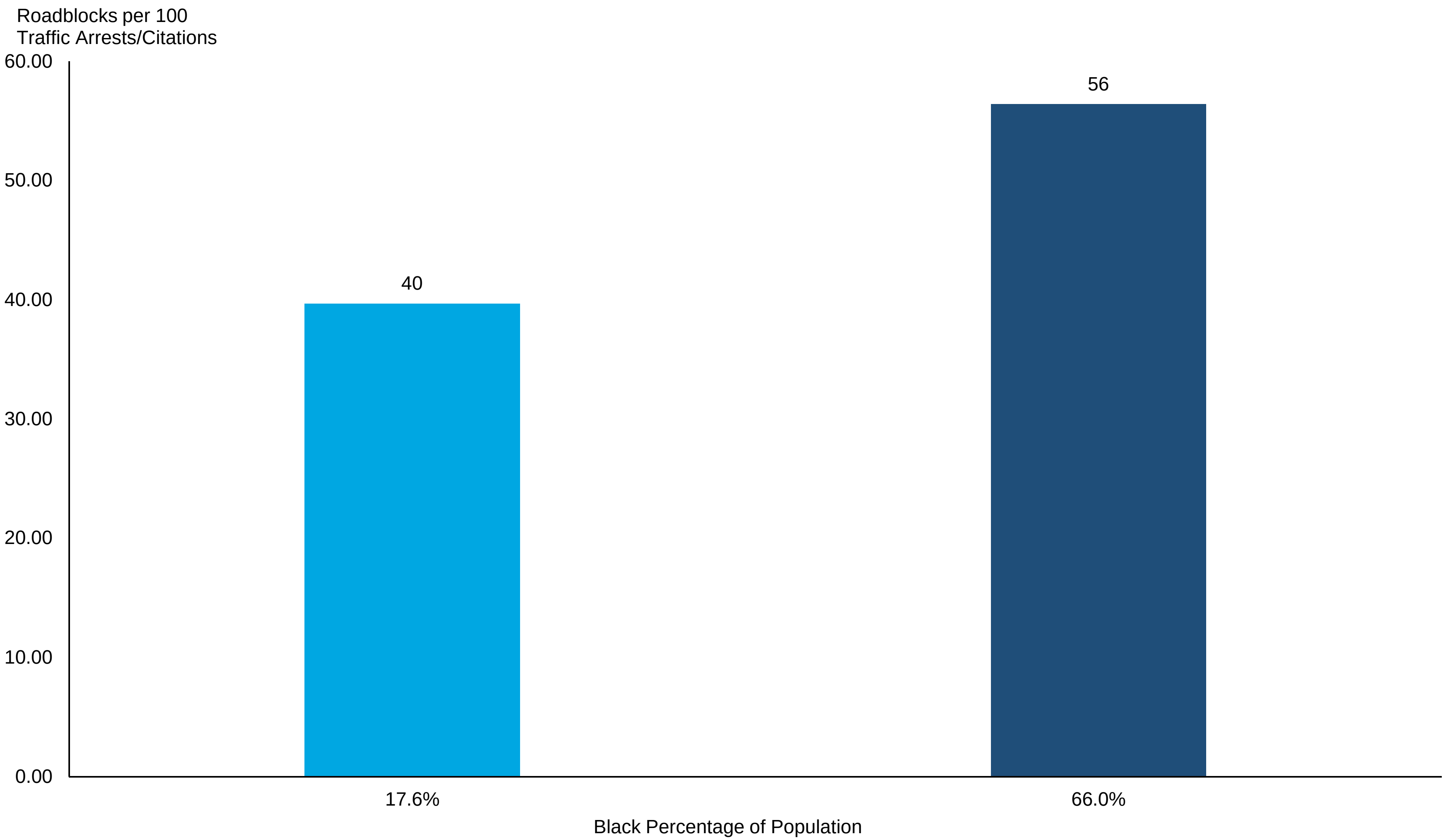


Source: Master CAD Report - To Be Produced.csv; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; American Community Survey Five Year Estimates, U.S. Census Bureau

Note: The Census Bureau has yet to release the 2013–2017 American Commiunity Survey Five Year Estimates. Data from the 2012–2016 American Community Survey Five Year Estimates are used for observations in both 2016 and 2017.

EXHIBIT 5

Roadblocks per 100 DUI and Traffic Violations by Racial Breakdown



Source: Master CAD Report - To Be Produced.csv; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; American Community Survey Five Year Estimates, U.S. Census Bureau

Note: The Census Bureau has yet to release the 2013–2017 American Commiunity Survey Five Year Estimates. Data from the 2012–2016 American Community Survey Five Year Estimates are used for observations in both 2016 and 2017.

EXHIBIT 6

Regression Results: Effect of Race on Frequency of Roadblocks, Controlling for Other Factors[1]

2012–2017

Variable[2]	(1) With DUI Arrests[3]	(2) With Traffic Citations/Arrests[4]	(3) With DUI Arrests and Traffic Citations/Arrests[5]
Black Percentage of Population	0.06492	0.05829	0.06218
standard error	0.01756	0.02486	0.01721
p-value	0.00033	0.02073	0.00044
Number of DUI Arrests Per 1,000 People	1.22070		1.38900
standard error	0.10390		0.12150
p-value	0.00000		0.00000
Number of Traffic Citations/Arrests Per 1,000 People		0.15220	-0.10300
standard error		0.04928	0.04075
p-value		0.00251	0.01281
Median Household Income (in Thousands)	0.03166	0.01685	0.02669
standard error	0.01588	0.02260	0.01566
p-value	0.04851	0.45750	0.09094
Unemployment Rate	-0.11910	-0.36860	-0.07771
standard error	0.07720	0.10540	0.07727
p-value	0.12550	0.00066	0.31660
Percentage of Households with At Least One Vehicle	-0.05640	-0.33580	-0.09574
standard error	0.07273	0.10080	0.07282
p-value	0.43960	0.00115	0.19120
Percentage of Population between Ages 15-24	-0.03368	-0.08256	-0.04544
standard error	0.04824	0.06838	0.04742
p-value	0.48640	0.22970	0.33980
Constant	2.58350	33.99400	7.05080
standard error	7.80860	10.80700	7.83940
p-value	0.74130	0.00209	0.37030
Observations	126	126	126
Adjusted R-Squared	0.646	0.293	0.662

Source: Master CAD Report - To Be Produced.csv; American Community Survey Five Year Estimates, U.S. Census Bureau

Note:
[1] All Specifications include only CAD Roadblocks.
[2] The Census Bureau has yet to release the 2013–2017 American Commiunity Survey Five Year Estimates. Data from the 2012–2016 American Community Survey Five Year Estimates are used for observations in both 2016 and 2017.
[3] Specification (1) uses number of DUI arrests per 1,000 people per year by census tract as a control variable.
[4] Specification (2) uses number of traffic citations and arrests per 1,000 people per year by census tract as a control variable.
[5] Specification (3) uses both number of DUI arrests and number of traffic citations and arrests as control variables.

APPENDIX A

BRYAN RICCHETTI, Ph.D.
Vice President

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ACADEMIC BACKGROUND

9/02 – 7/07 **Cornell University** Ithaca, New York

Ph.D., Economics, Applied Econometrics, Labor Economics

9/95 – 5/99 **Hamilton College** Clinton, New York

B.A., Economics with Honors, Magna Cum Laude, Phi Beta Kappa

PROFESSIONAL EXPERIENCE

9/07 – Present **Cornerstone Research, Inc.** Chicago, Illinois

Vice President

- Manage and conduct economic analysis for complex business litigation and regulatory matters, with specialization in antitrust, labor, class action, market manipulation and product misrepresentation matters.
- Expertise applying a wide range of empirical and theoretical methods to complicated market settings, including the application of statistical methods to analysis of large, proprietary data sets.
- Industry focus includes: retail, food and agriculture, the economics of distribution, and sports economics.

Selected Consulting Experience

- *Wage Discrimination Matter* Analyzed claims of gender discrimination. Oversaw the statistical analysis of wage and promotion patterns in internal personnel records for one of the largest employers in the world.
- *Monopsony Wage Fixing Cartel in Sports Industry* Analyzed claims that wages were capped by a sports regulatory organization. Oversaw statistical analysis of key issues.
- *Monopsony Wage Fixing Cartel in Service Industry* Analyzed claims of monopsony wage suppression in service industry. Managed and implemented statistical analysis of complex payroll records. Conducted liability and damages analysis.

- *Wage Discrimination Consulting Matters* Analyzed wage and promotion patterns in internal personnel records for large private company. Implemented econometric tests.
- *Wrongful Termination Gender Discrimination Matter* Analyzed wage and job history data to assess damage claims for employees who were allegedly wrongfully terminated by employer.
- *Alleged Cartels in Dairy Industry* (*Alice H. Allen et al. v. Dairy Farmers of America, Inc., et al. and Sweetwater Valley Farm, Inc., et al., v. Dean Foods Company, et al.*) Analyzed liability, damages, and class certification issues in multiple cases alleging vertical and horizontal conspiracies, price-fixing and quantity restrictions in the dairy industry. Analyzed pricing data at all levels of the industry, including issues of pass-trhough. Oversaw implementation of econometric analysis.
- *Alleged Monopoly and Foreclosure in Home Recreation Industry* Assessed claims of attempted monopoly and foreclosure by large distributor of home recreation products. Developed statistical model of damages to measure alleged impact of challenged conduct.
- *Merger in Food and Agriculture Industry* Analyzed potential economic impacts of a proposed merger between two large distributors. Assessed industry structure, competitive landscape, and possible price effects.
- *Regulatory matters involving state-level alcohol laws* Analyzed the economic impact of changes to state-level laws related to the distribution of beer, wine, and liquor in one state, and retail sale of liquor in another state. Assessed the potential effect of law change on alcohol consumption, tax revenue, and relevant social and economic outcomes.
- *LIBOR Manipulation Matters* Conceptualized and managed econometric analysis to understand the effect of the alleged conduct on rate trends. Prepared findings for regulatory investigation.

9/03 – 9/07 **US Census Bureau, LEHD** Ithaca, New York

Labor Economist

- Conducted econometric analysis related to research program on data confidentiality. Performed complex statistical modeling of key labor market outcomes. Authored internal papers and presentations.

7/99 – 7/2002 **MDRC** New York, New York

Research Assistant

- Conducted economic and statistical analyses of the effect of welfare-to-work programs on labor market outcomes.

TESTIMONY

Wal-Mart Puerto Rico, Inc. v. Juan C. Zaragoza-Gomez U.S. District Court, District of Puerto Rico. Retained by counsel for Plaintiff. Analyzed statistics issue. Filed affidavit on 1/19/16, deposed, and testified at trial.

Dunmars v. Board of Trustees of Community College District No. 510 and Jorie Menclewicz U.S. District Court, Northern District of Illinois, Eastern Division. Retained by counsel for Plaintiff. Damages analysis in lost wages matter. Report filed on 3/18/16.

Scott Swanson v. Epic Systems Corporation U.S. District Court, Western District of Wisconsin. Retained by counsel for Defendant. Rebuttal of Plaintiff expert regression analysis in age discrimination matter. Report filed on 9/5/17.

Boston Chapter, NAACP, Inc., et al. v. Nancy B. Beecher et al., and *Pedro Castro er al., v. Nancy B. Beecher et al.*, U.S. District Court, District of Massachusetts. Retained jointly by Plaintiffs and Defendants. Analysis of qualified labor pool for entry-level police and firefighers. Report filed on 10/11/17.

Winn-Dixie Stores, Inc. and Bi-Lo Holdings, LLC v. Southeast Milk, Inc., et. Al, U.S. District Court, Middle District of Florida, Jacksonville Division. Retained by counsel for Defendants. Analyzed liability and damages in alleged horizontal quantity restriction conspiracy. Report filed on 2/20/18.

Data Breach matter. Retained as statistics expert to analyze patterns of alleged data breach. Case resolved before report or testimony.

Antitrust matter. Retained to analyze procompetitive aspects of allegedly anticompetitive horizontal agreement. Case resolved before report or testimony.

ARTICLES AND PRESENTATIONS

Moderator, "The Capper Volstead Act - Lessons from the Trenches," ABA Teleconference Panel, December 9, 2016.

Panelist, 43rd Annual Fordham Conference on Antitrust Law and Policy, Economic Workshop – "Preparing for Deposition and Dealing with *Daubert* Challenges"

Expert Witness, ABA Antitrust Spring Meetings Mock Trial, Spring 2015 (Case involved antitrust issues raised by a hypothetical college athletic association's restrictions on amateur player compensation)

Expert Witness, Antitrust Law & Economics Institute for Federal Judges Mock Trial, October 2015 (Case involved antitrust issues raised by a hypothetical college athletic association's restrictions on amateur player compensation)

Co-author, "Applying Econometrics to Assess Market Definition and Market Power," *Econometrics: Legal, Practical, and Technical Issues,* American Bar Association Section of Antitrust Law.

Co-author, “Antitrust Impact in Indirect Purchaser Class Actions: The Need for Rigorous Analysis of Pass-Through,” in the forthcoming Spring 2015 ABA Antitrust Distribution and Franchising Committee Newsletter

“Interpreting Comcast: Judge Koh’s Decision in Brazil v. Dole Foods,” in the Winter 2015 ABA Agriculture and Food Committee Newsletter.

Contributor, “How Effective Are Different Welfare-to-Work Approaches? Five-Year Adult and Child Impacts for Eleven Programs.” December 2001, New York: MDRC.

Co-Author, ABA Handbook, Chapter on Pricing Regulations in the Dairy Industry, *Forthcoming.*

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ACADEMIC HONORS AND AWARDS

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Scholarship Prize in Economics, Hamilton College	Spring 1998

Documents Considered by Bryan Ricchetti, Ph.D.

Legal Pleadings

Answer and Affirmative Defenses of Defendants, Madison County, Mississippi and Sheriff Randall C. Tucker, In His Official Capacity, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities,* CIVIL ACTION NO. 3:17-cv-347 WHB LRA.	June 29, 2017
Class Action Complaint for Declaratory and Injunctive Relief and Individual Damages, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities,* CIVIL ACTION NO. 3:17-cv-347 WHB LRA.	May 8, 2017
Defendants' Memorandum of Authorities in Opposition to Plaintiffs' Motion to Compel, *Latoya Brown; Lawrence Blackmon; Herbert Anthony Green; Khadafy Manning; Quinnetta Manning; Marvin McField; Nicholas Singleton; Steven Smith; Bessie Thomas; and Betty Jean Williams Tucker, individually and on behalf of a class of all others similarly situated, v. Madison County, Mississippi; Sheriff Randall S. Tucker, in his official capacity; and Madison County Sheriff's Deputies John Does #1 through #6, in their individual capacities,* CIVIL ACTION NO. 3:17-cv-347 WHB LRA.	November 3, 2017
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APPENDIX B

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Data

American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi, Age and Sex	2012–2016
American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi, Employment Status	2012–2016
American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi, Housing Characteristics	2012–2016
American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi, Median Household Income	2012–2016
American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi, Race	2012–2016
American Community Survey Five Year Estimates for All Places in Madison County, Mississippi, Demographic and Housing Estimates	2016
American Community Survey Five Year Estimates for All Census Tracts in Madison County, Mississippi - Geodatabase Format, Shapefiles, available at *U.S. Census Bureau,* https://www.census.gov/geo/maps-data/data/tiger-data.html.	2015
Tiger/Line Shapefiles: Places - Mississippi, available at *U.S. Census Bureau*, https://www.census.gov/cgi-bin/geo/shapefiles/index.php?year=2017&layergroup=Places.	2017
"Master CAD Report − To Be Produced.csv."	2012–2017
"Roadblock Locations (Handwritten).xlsx."	2012–2017
"Unlisted Roadblocks.xlsx."	2012–2017
"2010 Census Tallies of Census Tracts, Block Groups & Blocks," available at *U.S. Census Bureau,* https://www.census.gov/geo/maps-data/data/tallies/tractblock.html.	2010
"2010 Census – Census Tract Reference Map: Madison County, MS," available at *U.S. Census Bureau,* https://www2.census.gov/geo/maps/dc10map/tract/st28_ms/c28089_madison/DC10CT_C28089_001.pdf	2010

Other

Sobriety Checkpoint Guidelines, Policy and Procedure, MC-RFP 2-1–MC-RFP 2-4

APPENDIX C

Regression Sensitivity of Number of Roadblocks Per 1,000 People by Census Tract

Variable[1]	(1) Incl. Handwritten Roadblocks[2]	(2) Incl. Additional Roadblocks[3]	(3) Including All Roadblocks[4]	(4) 2014–2017[5]	(5) 2015–2016[6]
Black Percentage of Population	0.06133	0.06200	0.06115	0.08651	0.11160
standard error	0.01859	0.01750	0.01925	0.02308	0.03285
p-value	0.00128	0.00057	0.00190	0.00035	0.00176
Number of DUI Arrests Per 1,000 People	1.61590	1.54120	1.76810	1.41100	1.50490
standard error	0.13130	0.12360	0.13600	0.15040	0.19820
p-value	0.00000	0.00000	0.00000	0.00000	0.00000
Number of Traffic Citations/Arrests Per 1,000 People	-0.12270	-0.11190	-0.13170	-0.11260	-0.15470
standard error	0.04402	0.04146	0.04560	0.05176	0.07730
p-value	0.00618	0.00795	0.00461	0.03268	0.05332
Median Household Income (in Thousands)	0.02594	0.02261	0.02187	0.04232	0.05838
standard error	0.01692	0.01593	0.01752	0.02104	0.03049
p-value	0.12780	0.15840	0.21450	0.04782	0.06394
Unemployment Rate	-0.09300	-0.09165	-0.10690	-0.08406	0.01836
standard error	0.08346	0.07860	0.08645	0.11340	0.16420
p-value	0.26740	0.24600	0.21850	0.46080	0.91160
Percentage of Households with At Least One Vehicle	-0.09488	-0.08740	-0.08654	-0.09099	-0.21380
standard error	0.07866	0.07408	0.08148	0.10020	0.15200
p-value	0.23020	0.24040	0.29030	0.36680	0.16860
Percentage of Population between Ages 15-24	-0.04124	-0.05159	-0.04739	-0.01959	-0.09472
standard error	0.05122	0.04823	0.05305	0.05941	0.08334
p-value	0.42230	0.28690	0.37350	0.74240	0.26370
Constant	7.11280	6.74560	6.80770	4.18290	15.08500
standard error	8.46820	7.97440	8.77090	10.62100	16.21300
p-value	0.40260	0.39930	0.43920	0.69480	0.35870
Observations	126	126	126	84	42
Adjusted R-Squared	0.683	0.695	0.704	0.666	0.741

Source: Master CAD Report - To Be Produced.csv; Roadblock Locations (Handwritten).xlsx; Unlisted Roadblocks.xlsx; American Community Survey Five Year Estimates, U.S. Census Bureau

Note:
[1] The Census Bureau has yet to release the 2013–2017 American Community Survey Five Year Estimates. Data from the 2012–2016 American Community Survey Five Year Estimates are used for observations in both 2016 and 2017.
[2] Specification (1) includes only CAD Roadblocks and Handwritten Roadblocks.
[3] Specification (2) includes only CAD Roadblocks and Additional Roadblocks
[4] Specification (3) includes all CAD Roadblocks, Handwritten Roadblocks, and Additional Roadblocks.
[5] Specification (4) includes only CAD Roadblocks that occurred between 2014–2017.
[6] Specification (5) includes only CAD Roadblocks that occurred between 2015–2016.