Looking Beyond the Veil of Darkness:

Police Traffic Citation Bias in Ferndale, MI

by

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Abstract

With the support of the City of Ferndale and the Ferndale Police Department, I conducted research into possible police bias in traffic citations to help end a stalemate between activists and officers, and chart a path towards reform if bias was found.

After accessing and filtering the citation records furnished by the Ferndale Police Department, I began a preliminary “Veil of Darkness” study on 2016 traffic stops. That study was later expanded to include data from 2011 through 2017, and then compared with an analytical model based on adjusted census data.

I found that while the observed police bias did not match the levels suggested by the Michigan chapter of the American Civil Liberties Union (Associated, 2014), there is tentative evidence of racial bias against black drivers. When expanded to 7 years, the Veil of Darkness method did not show bias. However, the adjusted census benchmark showed that black drivers are cited at rates nearly 20 percentage points higher than expected from a representative sample. In addition, I found that black women were more likely to be cited than black men, and young black drivers ages 16-24 were more likely to be cited than older black drivers.

Keywords: Veil of Darkness, traffic stop analysis, adjusted census, police bias

Introduction

Each year over 20 million Americans are stopped by police for traffic violations, making it one of the most common ways for people to interact with police (Langton and Durose, 2013). With these stops comes a longstanding and widespread belief that black drivers are more frequently stopped by police (Newport, 1999), a belief that has been confirmed by national findings (Pierson 2017). More recently, tensions between the public and police have been exasperated by incidents of police violence in Ferguson, Baltimore, Chicago, Sacramento, and elsewhere, along with social movements like Black Lives Matter (NPR, 2017). Ferndale, MI, is no exception. In 2014, those national tensions reached a local flashpoint when the Michigan chapter of the American Civil Liberties Union (ACLU) accused the Ferndale Police Department of racial bias based on traffic citation records (Associated, 2014). Ferndale officers denied the accusation, pointing out that Ferndale is a major conduit of traffic from neighboring cities such as Detroit, with significantly different racial demographics (Collins, 2017). The incident left activists and police officers at an impasse, with no clear way to resolve their differences.

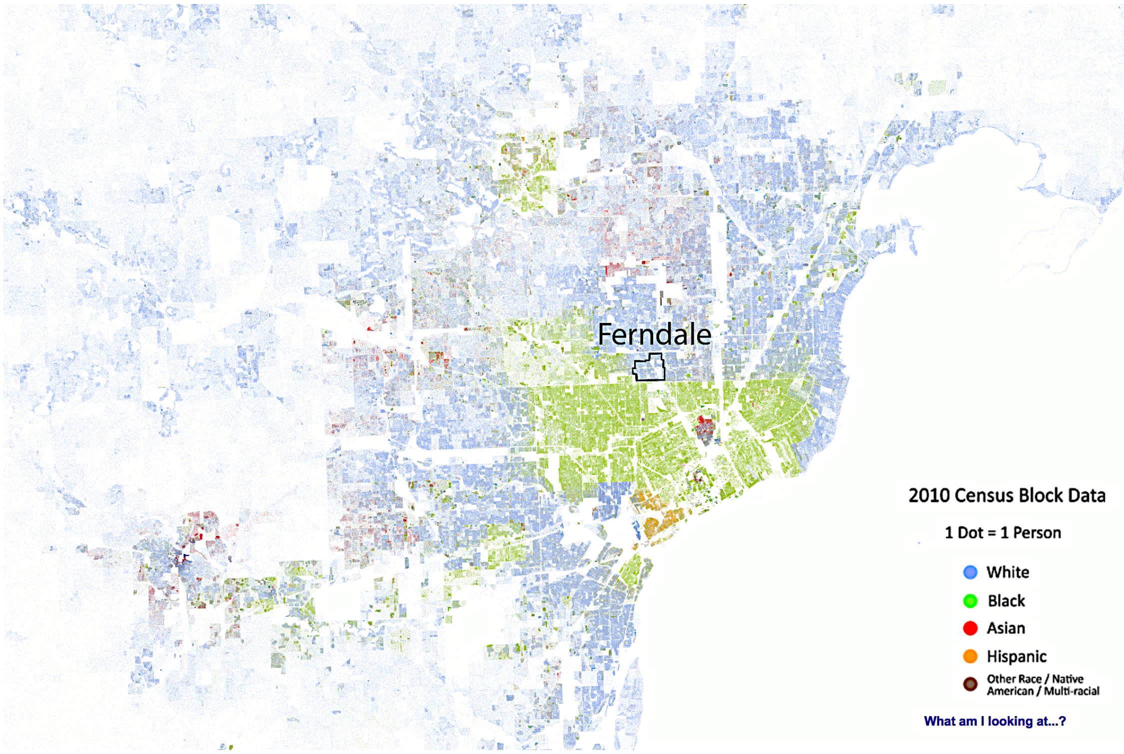
While police bias exists in the United States on a national level, it may not be an issue in every department. But how do we detect and quantify that bias in specific areas? Was the ACLU correct in its assertions for Ferndale, and to what extent? And how can smaller cities like Ferndale find answers to these questions with their limited data, time, and resources? In this paper, I will show that while some cost-effective methods such as the Veil of Darkness are problematic, others such as adjusted census statistics can offer a way forward.

Available data and how it can be used

When interest in racial bias in traffic stops and “driving while black” peaked in the 1990s and 2000s, there was a surge in state laws mandating the collection of data on routine stops to better measure and address bias (Baumgartner, 2017). However, the reach of these laws was far from universal. And while departments nationally record information about traffic stops that result in a citation or arrest, many departments do not record information about stops without citations or arrests.

Even when data is available, detecting bias is problematic. The primary difficulty is defining a benchmark of citations per racial group assuming no police bias, to compare against the observed percentages of minority citations seen in the police data. In the most basic case, the percentage of black drivers is simply compared to the percentage of black residents in the city population (Cox, 2001). This was the ACLU approach in their 2014 analysis. But when minority populations are highly segregated in the surrounding areas, as they are in Ferndale (see Figure 1), this can produce misleading results when much of the traffic through the city comes from the surrounding areas (Gau 2012).

Figure 1: This dot map illustrates the high level of racial segregation in the areas surrounding Ferndale. (Cable, 2013)



Other methods employed to define a benchmark include using the driving age population from the records of the Motor Vehicle Department or the National Personal Transportation Survey (Engel & Calnon, 2004), the use of automatically triggered cameras (Lange 2005), not-at-fault accident rates (Smith et al. 2003), hit-rates for the discovery of illegal contraband (Ridgeway, 2006), or direct observation of drivers from another car (Smith, 2003).

Direct observation is viewed as the preferred benchmark, but is rarely used due to its expense. In one estimate, conducting a single traffic survey requires 800 person-hours of labor (Pritchard, 2001). And even less intensive studies can still have a large cost. The city of San Diego paid researchers from San Diego State University $62,500 to examine traffic stop records over a two-year period using the Veil of Darkness method (Littlefield, 2016). These expenses make academically rigorous research on police bias particularly difficult for smaller communities like Ferndale that lack the capacity to employ analysts or hire consultants.

After a benchmark has been chosen, understanding the factors that lead to racial disparities in traffic stops is still complex. Researchers have suggested numerous confounding factors, sometimes overlapping. These include differences in minority driving patterns (Ridgeway, 2010), differences in rates of breaking the law (for example by having lower seatbelt use among population groups (Pickreall, 2010)), and differences in exposure to police in high-risk or highly-policed areas (Gelman, 2006). Police may also be engaging in "pretextual" stops, where officers stop a vehicle for a minor violation in order to search for additional criminal activity (Engel, 2002). While a legal tactic in the United States (Whren et al. v. United States, 1996), pretextual stops make untangling the motivation behind a particular stop difficult. And each of these factors can affect the integrity of the benchmark.

Methods selection for Ferndale

To overcome these challenges with a limited timeframe and budget, I used two independent methods to detect bias. First was the relatively recent technique called the "Veil of Darkness," initially described by Jeffrey Grogger and Greg Ridgeway in 2006. By comparing the driver demographics of citations given in the evening during daylight versus evening citations given in darkness (from approximately 5 to 9 pm). Using that timeframe, which during summer is in daylight and during winter is in darkness, we can compare one driving population with a single variable, visibility of the driver's race by officers. We can then conclude that if officers are giving citations to black drivers more frequently in daylight versus in darkness, it indicates bias against black drivers when their race can more easily be seen.

The second method was an analytical approach using adjusted census data at the zip code level. As discussed, comparing Ferndale census data to citations does not address the segregation of neighboring communities. To account for those disparities, I compared the census demographics results by the zip code of each driver.

I then adjusted the census data further to reflect only the working population (age 16 and up) with access to at least one vehicle in each zip code. Adjusting for vehicle access by zip code is also important because vehicle access varies with access to public transportation. People with more public transportation options are less likely to own vehicles (Valenzuela, 2000). This method was chosen to validate the perceived risks of the Veil of Darkness method, which has many assumptions embedded into it.

For both the Veil and census methods, data was analyzed for all citations available, by year and then in total, then separated by gender to compare male and female drivers, then by age to compare youth aged sixteen to twenty-four with adults aged twenty-five and older.

Related Work

The problem of racial bias by police in the United States has long been noted by academics. Economist Gary Becker proposed a test for racial bias as far back as 1957 (Becker, 1957). And in addition to latent racism, the argument was often made in the 1980s and 90s that the “War on Drugs” contributed to police disproportionately targeting minorities in traffic stops (Warren, 2006). Later, concern with “driving while black” built into a surge of state traffic stop data laws in the early 2000s (Baumgartner, 2017).

Despite this long history of interest, rigorous study of police bias has been slow to develop. In 2001, Smith and Petrocelli stated, “Most of the existing research on racial profiling has been descriptive in nature and has been conducted by law enforcement agencies or interest groups. This research has not been subjected to peer review, nor has it been published in academic or scholarly journals” (Smith, 2001). Engel also pointed out that the academic and government research that had been done lacked theoretical claims and development (Engel, 2002).

More recently, sustained interest and pressure has produced a growing body of literature, though with mixed results. Some studies have shown that black drivers are no more likely to be given citations than white drivers (Novak 2004). While others have indicated that race is a significant factor among a number of variables (Barnum, 2010; Ingram, 2007; Tillyer, 2013). Results have been mixed even within a single study. An example from North Carolina found race to be a predictor of stops for local police, but not for Highway patrol officers (Warren 2006).

Other variables found to be significant predictors of traffic stops have included driver age (Warren 2006), driver gender (Smith 2003), time of day (with more stops being made in the evening (Smith, 2001)), and the driver being a minority in the area they're stopped in, regardless of race (Withrow, 2004). Driving behavior and previous contact with police have also been predictive factors (Lange, 2005; Lundman 2003). Of two studies that focused on both race and gender in traffic stops (Farrell 2015; Vito 2017), one found that leniency towards female drivers decreased as the police department hired more female officers, and that black drivers were less likely to receive minor speeding violations than white drivers. The other did not find significant disparities between genders. Most significantly, the Stanford Open Policing Project analyzed over 60 million state patrol stops in 20 states between 2011 and 2015 and found that black drivers are stopped proportionally more often than white drivers (Pierson 2017).

Studies focused on citations given after stops were initiated have also shown mixed results. Engel & Calnon found a number of factors that were positively associated with being issued a citation, including being a man, being young, being a person of color, having had few previous stops, and having fewer passengers in the vehicle (Engel & Calnon, 2004). In contrast, Ridgeway found no correlation between minority drivers and the issuance of citations, though they were more likely to have a longer stop (Ridgeway 2006). More recently a study of one anonymous police department found that young black drivers were more likely to receive a warning and a citation than white drivers (Tillyer, 2013). And a review of 1 million traffic stops in Montgomery County, MD, suggested Hispanics are significantly more likely to receive tickets than either white or black drivers (Economist, 2017).

Veil of Darkness Research

The newest technique employed by some researchers is the Veil of Darkness analysis. A Veil of Darkness study attempts to address the expense of setting up a control group by comparing only traffic stops at times of the day which are sometimes in light, and sometimes in darkness depending on the season (the “intertwilight” period). It relies on the assumptions that traffic at similar times is demographically consistent across seasons, and that police will have a harder time identifying and profiling minorities in darkness. This technique was first suggested by Jeffrey Grogger and Greg Ridgeway in their 2006 paper, Testing for Racial Profiling in Traffic Stops from behind a Veil of Darkness. It has now been applied in 6 jurisdictions: Oakland, CA (Grogger, 2006; Oakland Police Department, 2004), Cincinnati, OH (Ridgeway, 2009), Minneapolis, MN (Ritter, 2009), Syracuse, NY (Worden, 2012), Connecticut (Ross, 2015), and Durham, NC (Taniguchi, 2017). The original Oakland study used 6.5 months of traffic stops in one year, while later studies used 2 to 6 years. The plurality of studies did not find evidence of police bias for any year.

While a relatively recent method, it is not without limitations, and has attracted considerable criticism. Common critiques include that it assumes that officers can easily tell the race of the driver during daylight hours before stopping them, that traffic patterns do not differ by daylight availability (Johnson, 2017), that driving patterns, and thus exposure to police, is the same before and after dark and do not vary by race, and that the racial distribution of drivers is the same before and after dark. It also assumes that officers are not using proxies for race, such as vehicle type or condition that would be discernable even in darkness (Miller, 2007).

Trends in census benchmarking

Historically, "[m]ost jurisdictions appear to be benchmarking their police-citizen contact data against unadjusted census data" (Fridell, 2004). Cox's 2001 Interim report of traffic stops statistics for the state of Connecticut, for example, uses this method with some modifications. But by 2004, the Police Executive Research Forum (PERF) and the U.S. Department of Justice's Office of Community Oriented Policing Services (COPS Office) were actively calling for the minimum acceptable standard to be adjusted census benchmarking, noting that "researchers can draw no definitive conclusions regarding racially biased policing" using unadjusted numbers (Fridell, 2004). Since then a variety of studies have used adjusted census numbers, for example West Virginia (Haas 2008). However, the larger trend has been to avoid the ambiguities of census benchmark studies by using methods such as the veil of darkness and direct traffic observation, or to used adjusted census numbers in combination with other methods (Ross, 2015).

Studies in Michigan

In Michigan, the Michigan Association of Chiefs of Police opposed mandatory data collection for traffic stops and citations during the height of their popular implementation (Portis, 2001). As a result, the Michigan State Police did not start routinely recording the race of drivers for all traffic stops until 2016 when they began to do so voluntarily (Thorp, 2016). This has left Michigan with a patchwork of different standards and levels of recorded data. Cities such as Lansing have taken a proactive approach, releasing regular reports on racial bias in traffic stops (Carter, 2010). While others like Kalamazoo have released intermittent studies

(Lamberth, 2013), or released traffic stop data only after complying with FOIA requests (Associated, 2014). Like much of the United States' 18,000 law enforcement agencies (Banks, 2016), most departments in Michigan have not participated in any traffic bias studies.

It was in this context that in 2014, the Michigan chapter of the American Civil Liberties Union (ACLU) accused the Ferndale police of racial bias based on a FOIA request (Associated, 2014). After receiving basic traffic stop data, the ACLU reported that 60% of drivers cited by Ferndale police were black, while less than 10% of Ferndale residents are black, and requested the Ferndale Police Department conduct an inquiry into their findings (Associated, 2014).

These results illustrate the difficulty of accurately detecting police bias. The problem with the method used by the ACLU (unadjusted census benchmarking) is that many of the drivers who are cited by police may not live in the same area that they are being pulled over in. In the case of Ferndale, the records show that less than 5% of citations in 2014 were for Ferndale residents, while a full 18% were from Detroit. It also does not take into account racial disparities in vehicle availability, age, or gender. Because of these issues, and the considerable potential expense of a traffic study, Ferndale police were reluctant to agree to full study requested by the ACLU, resulting in a relative stalemate between officers and advocates (Collins, 2017).

Data Sources

On October 17th, 2017, Sgt. Baron Brown and Chief Tim Collins of the Ferndale Police Department—as well as April Lynch and Joseph Gacioch, the Ferndale city managers—approved the Ferndale Police Traffic Stop analysis after some negotiation with myself, granting access to the Courts and Law Enforcement Management Information System (CLEMIS) database. Data for 2016 was originally received from Tamica Brooks, the Ferndale Police Department Records Coordinator.

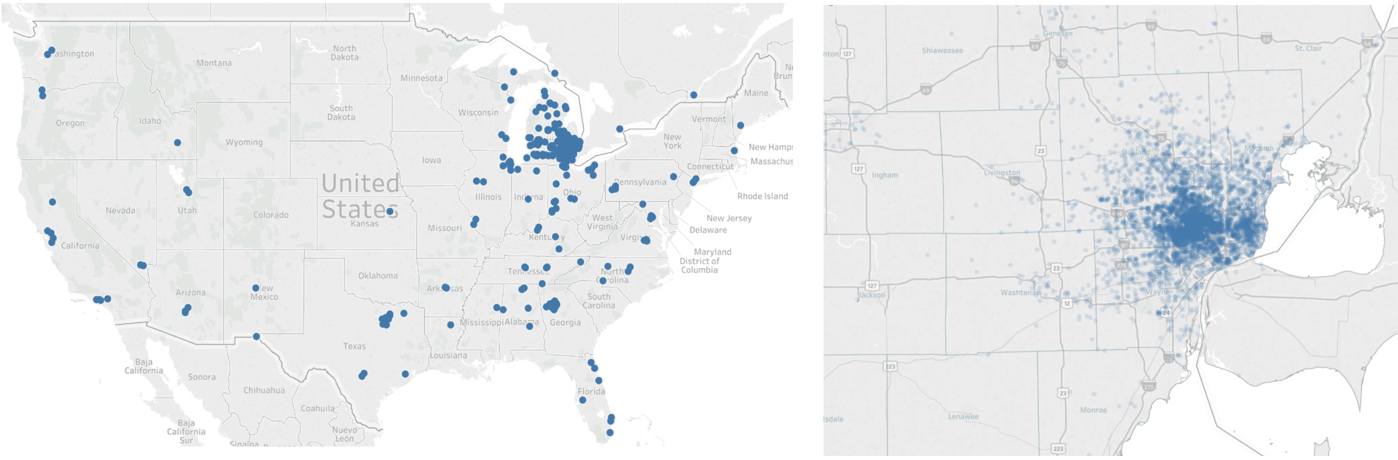
The Ferndale Police Department Traffic Citations in 2016 consisted of 7,773 citation records over the course of the year. Additional cleaning of the data was done, removing records that do not contain the race of the driver cited, or where the race was "unknown." As there was only a small number of non-white or -black records, those were excluded as well, resulting in 7,688 records used for the first iteration of the study. Out of state licenses were also excluded, as they make up only a small portion of citation, 2%.

Two problems were found with this initial dataset. First, it included inactive citation records. In the CLEMIS system, records that are later modified are not edited in the system. Instead, a new record is made with the same Citation Number, but a different Agency Status setting. Because of this, the first-run analysis suffered from duplicate records. However, because the edits were more related to new officer training than the citation offense, the results were felt to be non-biasing (Palazzolo, 2018). Second, the record fields returned were incomplete and did not include the full dataset for 2016.

In response to these findings, I completed a more complete pull of the CLEMIS citations database from 2008 through 2017, using SAP BusinessObjects Web Intelligence. This resulted in 66 fields, and 214,865 unfiltered individual citation records. Years 2008-2010 were not included in the analysis because at the time, a labor dispute was ongoing between the Ferndale Police Union and the Ferndale City Council, resulting in the eventual layoff of 6 officers in 2010, as well as the transition to a new police chief. 2010 also saw the introduction of the Traffic Enforcement Unit, an overtime traffic enforcement opportunity for officers. And in 2011, the Directed Patrol Unit was introduced, which had officers assigned full time to traffic enforcement. All of these changes resulted in substantially more traffic citations being made in 2011-2017 compared to 2008-2010 (several thousand per year), making direct comparison between these periods impractical (Palazzolo, 2018). Years before 2008 were not available in CLEMIS.

Census data used was the MEANS OF TRANSPORTATION TO WORK BY SELECTED CHARACTERISTICS table (S0802) from the 2012-2016 American Community Survey 5-Year Estimates for 5-digit ZIP code tabulation areas (860) within or partially within the state of Michigan.

Figure 2: Plots of cited driver home address locations in 2016 (Ferndale, 2018)



These plots illustrate the geographic distribution of driver home locations who were cited in Ferndale. In general, they show an inverse distance weighting, meaning that distance from Ferndale is highly predictive of the odds of being cited. A full 98% of citations where the driver address is known are within Michigan.

Research Methodology

Selecting methods for detecting police bias is inherently an exercise in compromise. Miller & Guerin point out that, “[e]ven researchers with tremendous resources have a hard time coming to definite conclusions. All data collection processes used thus far have flaws” (Miller 2007). Selecting methods for Ferndale, MI, proved particularly difficult, because of additional constraints on the data available at the State and local levels. Table 1 summarizes the common methods used in the field to determine a benchmark, their availability, and their costs (see Related Work for details).

Table 1: Common methods for establishing a benchmark traffic racial makeup

Method	Unique data needed	Cost	Available in Ferndale
Census	None	N/A	Yes
Adjusted census	Home address	N/A	Yes
DMV	State records including race	N/A	No (race not recorded)
Cameras or direct observation	Large observation sample	800 person-hours & equipment	Yes
Traffic accident rates	Records including race	N/A	No (race not recorded)
Veil of Darkness	Accurate citation times	N/A	Yes

For our study the use of records from the Motor Vehicle Department or accidents was not possible because neither the State nor Ferndale police record the race of the driver in driver records or crash reports in CLEMIS, the department’s Courts and Law Enforcement Management Information System (Emmi, 2017). Comparisons between traffic stops with and without citations were also not possible because Ferndale does not routinely record stops that do not result in citations.

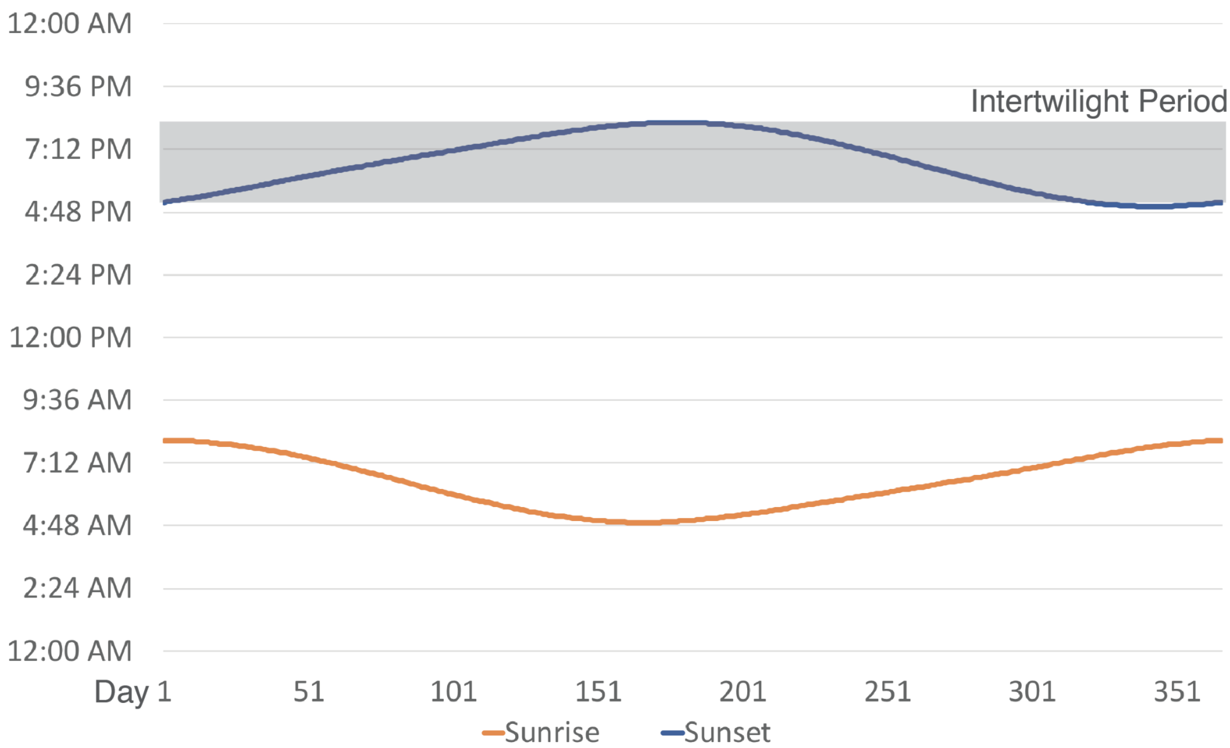
Despite its limitations, in the case of Ferndale using the Veil of Darkness provides two opportunities. First, the Ferndale data set allows us to do the longest longitudinal study yet done, with 7 full years' worth of citations (though with a considerably smaller dataset than Connecticut and others). And second, we can compare the results with another established method (in this case, an adjusted census benchmark). The previous six applications of the Veil of Darkness were not multi-modal, providing an opportunity to review how the Veil of Darkness method compares to other techniques.

With the support of the City of Ferndale and the Ferndale Police Department, I first conducted a preliminary "Veil of Darkness" study on 2016 traffic stops as a benchmark search for police bias. That study was then expanded to include data from 2011 through 2017, and validated with an analytical model based on adjusted census data.

Veil of Darkness

The "veil" is the assumption that when it is dark, police officers will have a more difficult time identifying the race of the driver prior to pulling them over. It also assumes that driving populations at given times of day do not change over the course of a year. It does this by using the periods of time that are sometimes in daylight and sometimes in darkness, called the intertwilight period. In 2016 for example, the evening intertwilight period for Ferndale, MI, (see Figure 3) was from 4:59 PM to 9:12 PM. A citation in August during this time would be in daylight, while in December it would be in darkness.

Figure 3: Sunrise and sunset times for Ferndale, MI, in 2016



First, as detailed in the Data Sources section, the Ferndale 2016 traffic stop data was cleaned resulting in 7,688 records.

Second, the data was pulled that pertained to the evening intertwilight period. Evening is used because most citations are given later in the day than the morning (Smith, 2001). Because we are looking at a narrow range of time, using the relatively larger evening sample size allows for more confidence in the results. The computations were done with a Python script that:

1. Calculates the sunset and dusk for that time and latitude/longitude for each stop
2. Calculates the intertwilight period for the data
3. Marks the stops as either occurring during the day or night
4. Filters the stops to the intertwilight period

The evening intertwilight period resulted in 1,137 records to be analyzed (see Figure 4). To ensure that citations were either clearly in dark or light, records after sunset but before night (civil twilight) were excluded to reduce ambiguity about driver visibility to officers.

Daylight and darkness were compared using a two-sample difference of proportions calculation to determine the relevance of daytime versus nighttime on the rate of black driver citations. Finally, a binomial generalized linear model was fit to confirm relevancy and calculate the odds ratio, which is interpreted as the change in probability of a black driver receiving a traffic citation in daylight versus darkness (Table 4). The use of a binomial model makes these odds ratios the inverse of odds for white drivers.

This process was then repeated for the expanded dataset, running the veil analysis for each year, and then again across all years. It was run for all citations available, then separated by gender to compare male and female drivers, then by age to compare youth aged sixteen to twenty-four with adults aged twenty-five and older.

Adjusted Census Benchmark

Because of the concerns with the Veil of Darkness method, I ran a parallel analysis using adjusted census data. The fewer assumptions with this model make it useful to validate the results of the Veil analysis. Adjusting the census statistics is important for several reasons. First, racial groups are not equally represented in different zip codes, so finding the proper comparison means separating citations by area of driver origin. This is particularly important when minority populations are highly segregated in the surrounding areas, as they are in

Ferndale (see Figure 1). Studies have also confirmed that much of the traffic through any city is from the surrounding areas, not just its own residents (48% non-residents in one study (Gau 2012), and 95% non-residents for Ferndale).

Second, racial groups are not equally represented within the driving population. One study based on 1990 census data reported that, “on average, more than 30 percent of Black households do not own vehicles, and in central cities the number is over 37 percent” (Pisarski, 1996). Over the next twenty years, this disparity leveled off, but remains steady at 20% of black households nationally without access to a vehicle, compared to 10% of white households (Murakami, 2013). Because vehicle ownership naturally correlates with driving quantity, this suggests that minority drivers drive less and represent a smaller pool of the population to be cited by the police. Direct measures from the National Household Transportation Survey indicate that African Americans average slightly fewer “vehicle trips per day” than white households, again confirming this hypothesis (see Table 2).

Table 2: Measures of Mobility by Race (Santos, 2009)

	Non-Hispanic White	**African American**	**Other Non-Hispanic**	**Hispanic**
Daily Person Trips/Household	9.13	9.46	10.26	11.72
Daily Vehicle Trips/Household	5.74	5.09	5.65	5.92
Person Miles Traveled/Household	92.34	81.37	94.16	87.63
Vehicle Miles Traveled/Household	55.81	47.65	55.23	52.31
Average Person Trip Length (miles)	10.22	8.97	9.43	8.06

Average Vehicle Trip Length (miles)	9.79	9.59	9.89	9.23

For Ferndale, I adjusted the census data of each zip code in Michigan to reflect these disparities (98% of citations where the driver address is known are within Michigan). We take the household information on average number of working people (age 16 and up) per racial group, and multiply that by the number of people in that zip code with access to a vehicle. In this way, for example, if 25 citations are from Ferndale residents, and 100 are from Detroit, we can predict that two of the Ferndale drivers would be black (Ferndale is majority white), and 80 of the Detroit drivers would be black (Detroit is majority black), if the drivers cited were a random sample. We would thus expect to see 82 black drivers cited in the police data.

I then subtracted the number of individuals without access to a vehicle for each race. This provides an individual estimate on vehicle access, allowing us to compare the census and citation results to look for bias. Adjusting the results is essential because an unadjusted benchmark will inaccurately predict a higher population of white drivers on the road (Fridell, 2004), which is verified by the Ferndale results.

I then ran the benchmarks again separately for male and female samples to look for gender disparities. Finally, I ran the analysis separately for the 15-to-24 age group and for the 25 and older age group (Fridell, 2004) to consider age as a factor alongside race in being cited (see Appendix 1 for detailed results).

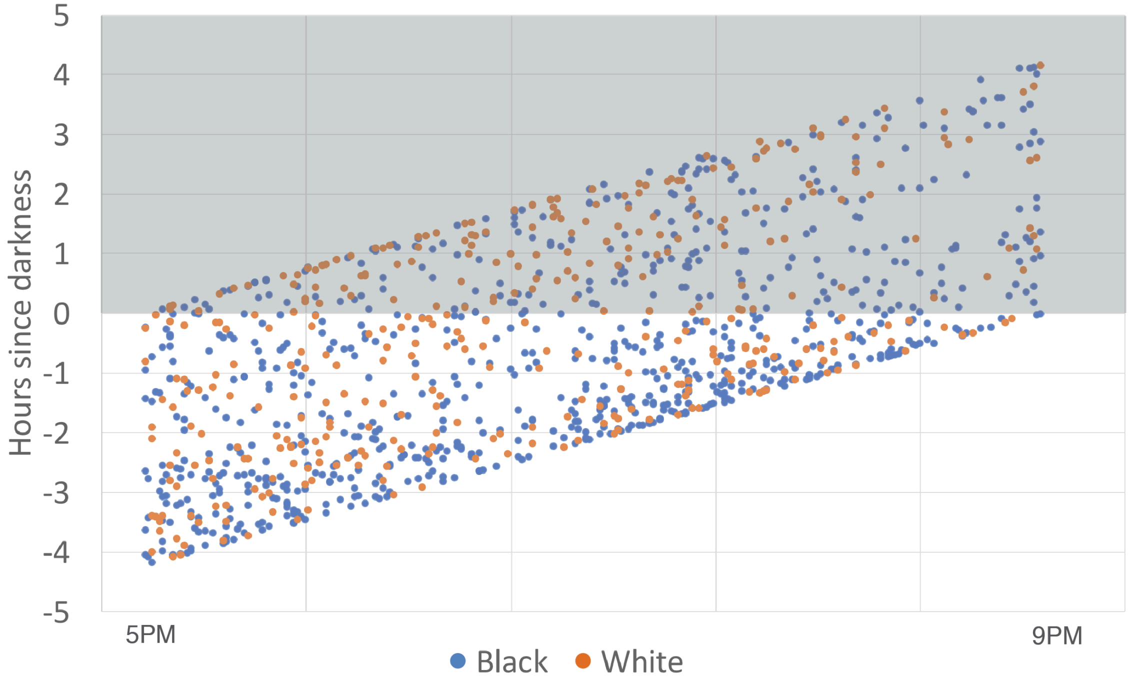
Results

2016 Veil of Darkness initial results

A preliminary Veil of Darkness analysis began with just 2016 citation data. I originally found that there was tentative evidence of police bias in giving traffic citations disproportionately to black drivers, if the assumptions of the "Veil of Darkness" method held for Ferndale.

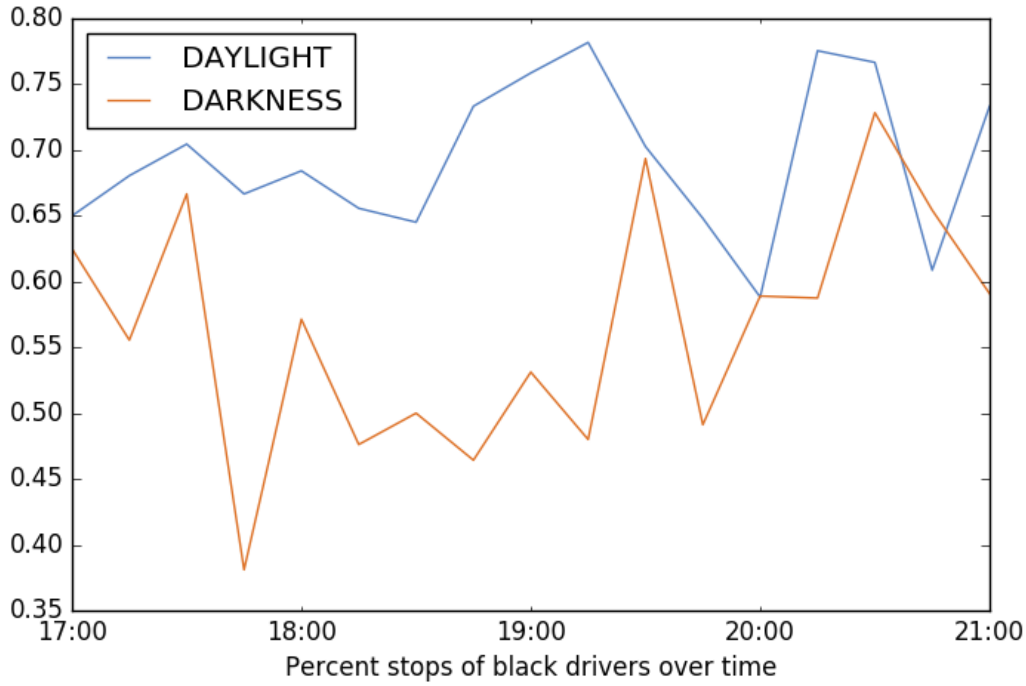
In the evening intertwilight period, 522 black drivers out of 731 total (71%) were given citations in daylight, while 248 black drivers out of 406 (61%) were given citations in darkness, showing a slight possible police bias against of black drivers compared to white drivers (see Figure 4). A two-sample difference of proportions test confirmed significance, with a p-value < 0.0001 (we reject the null hypothesis at $p < 0.05$).

Figure 4: Plot of traffic citation times by time and darkness



The shaded region indicates citations that were given after sunset. The figure includes the 1,137 citations given during the intertwilight period for both black and white drivers. Citations after sunset but before night (civil twilight) were excluded from the sample. If bias were present, one would expect the number of black citations to decrease in the shaded region in proportion to white citations.

Figure 5: Percent stops of black drivers, daylight and darkness



For each 15-minute interval during evening intertwilight, the blue line represents the percentage of citations in daylight that involve black drivers. The brown line represents the percentage of citations for black drivers in darkness. If bias existed, we would expect to see the percentage of black drivers cited in daylight higher than those cited at night. The total area between the two represents the bias observed.

Fitting a binomial generalized linear model confirmed the significance of daylight on the probability that black drivers are more likely to be cited by police in daylight versus darkness.

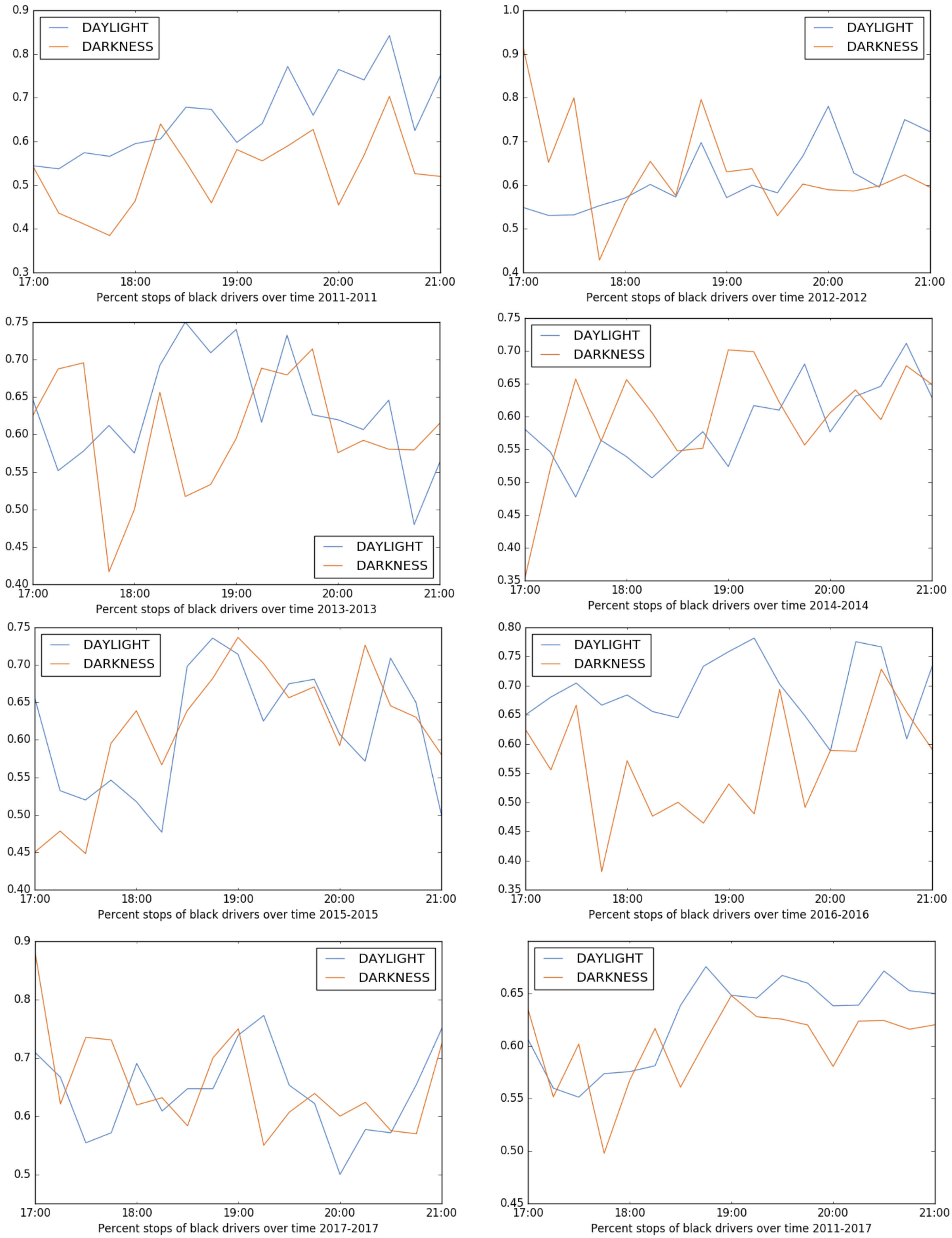
From that model, an odds ratio of 1.69 was calculated, meaning that black drivers are 1.69 times more likely to be stopped and cited by police during daylight than they are during darkness. These odds were inverted for white drivers. The 95% odds ratio confidence interval was 1.3 to 2.2.

2011-2017 Veil of Darkness

Running the Veil of Darkness analysis on the full data set produced starkly different results from the 2016 analysis. Expanding to 7 full years of data increased the citations count to 217,159 total records. Eliminating parking tickets (for which the race of the driver cannot be known) and other filters described above resulted in 128,289 records used. But rather than showing a clear increase in bias during the day, only two other years (2011 and 2014) showed any statistically significant difference of proportions. In addition, 2012 and 2014 show a reversal of the trend, with more black drivers being cited at night than during daylight in the intertwilight period. The variance in the results can easily be seen in figure 6.

Given this larger context, 2016 appears to be an outlier in the data, with fluctuations in results each year showing no intelligible pattern. This is made clear by running the analysis across all years, from 2011 to 2017. At this level, the variance washes out, and the proportion of black drivers cited during the evening intertwilight period during daylight and darkness is both 60%. Running the analysis by gender and age produces similar results; when the full time series is used, no difference can be seen. (see Appendix 2 for a full summary of results, including by gender and age).

Figure 6: Percent stops of black drivers, daylight and darkness



2011-2017 adjusted census benchmark

The adjusted census benchmark produced clearer results than the Veil of Darkness. I found that there was a statistically significant difference in expected percentage of black drivers, and the actual percentage of black drivers cited, for all years. On average, black drivers make up 59% of the drivers stopped and cited by Ferndale police. But if we took a random sample from the same zip codes that the drivers came from, we would expect to see only 39% black citations, a difference of 20 percentage points. In other words, a black driver is 1.5 times more likely to be cited by Ferndale police than an unbiased sample would suggest. Likewise, a white driver is 9% less likely to be cited than expected, resulting in a 29 percentage point spread between white and black drivers. These calculations are after adjusting for working adults with access to a vehicle in each Michigan zip code.

Looking at categories, we find that young black drivers aged 16-24 are slightly more likely to be cited than older black drivers, with 1.55 odds of being cited for young black drivers versus 1.49 for older black drivers. We also find that female black drivers are somewhat more likely to be cited than male black drivers, with 1.57 odds of being cited for female black drivers versus 1.43 odds for male black drivers. Young white drivers are slightly less likely to be cited than older white drivers, and female white drivers are the least likely to be cited out of all categories (see Appendix 1 for a full breakdown of results). These results remained consistent across individual years.

Discussion

Extending the Veil of Darkness study to all 7 years showed no clear evidence of police bias, and should serve as a warning about overconfidence. Had I stopped at 2016 using only one method, I would not have realized that 2016 was an outlier from the full data set. Extending the study and complementing the Veil with adjusted census numbers provided a clearer picture. The census analysis then found that a black driver is 1.5 times more likely to be cited by Ferndale police than an unbiased sample would suggest.

How should we interpret these results? At this stage, I can offer only speculation. But one hypothesis, based on my interactions with Ferndale, Detroit, and other neighboring officers during ride-alongs and interviews, is that Ferndale police believe there is a stark difference between Detroit and the outer ring of majority-white suburbs. These more affluent cities, with better-funded police departments, feel that in order to keep their own communities safe, they need to contain the high crime rate of Detroit within its city limits, and strictly police their boundaries. Because Detroit has the highest percentage of blacks among all major American cities, it is easy to imagine that this policing mentality could result in the biased citation numbers, even if the officers were not racially motivated.

Detecting and quantifying bias in specific departments rarely leads to satisfying conclusions. But the question remains, what can smaller communities like Ferndale do in order to address concerns like those raised by the ACLU? I believe that while some methods such as the Veil of Darkness are problematic, others such as adjusted census statistics can offer a way forward, providing a more fact-based foundation for further discussion and research.

Lack of traffic stops without citation

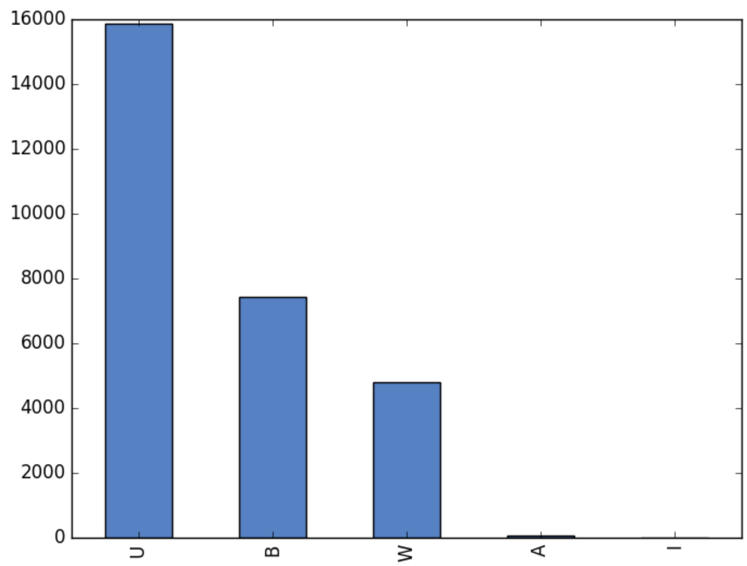
Perhaps one of the largest differences between the Ferndale data and many other traffic stop studies is the lack of a reliable measure of stops that result in a warning or no charge, versus ending with a citation. While Ferndale police are allowed to enter in stops without citation into the CLEMIS database, there is no departmental policy requiring officers to consistently log these stops (Brown, 2017). As a result, only approximately 300-400 of the citation records out of 217,159 are of stops not resulting in a citation, which were excluded from analysis. Because of this, I was not able to follow certain lines of inquiry, including racial profiling resulting in a disproportionate number of stops for minorities, or relative rates of citations after a stop (the "hit rate" or citation rate for stops by race).

It may be argued that not knowing the rate of total traffic stops, not just stops that result in citations, impacts the integrity of the study. However, for all possible scenarios of relationships between traffic stops without citations and traffic stops with citations, the observation of bias in the citations still holds. For example, if black drivers are being stopped and then not cited at lower rates than white drivers, and we then see that black drivers are still given higher rates of citations than white drivers, this indicates the actual level of bias is even higher than the citation numbers would suggest. Conversely, if black drivers are being stopped and not cited at higher rates than white drivers (possibly as a result of a stop-and-frisk strategy), and we still see that black drivers are given higher rates of citations than white drivers, this lowers the importance of the citation rate, because the biased judgment is actually happening in the choice to pull over the driver, rather than the choice to cite them. The presence of bias, however, does not change. Were no bias in citations found, not knowing the rate of stops without citations might weaken our conclusions. But because bias was observed, not knowing the rate of stops without citations does not necessarily invalidate those observations. In addition, Engel and Johnson argue that, "the appropriate conclusions researchers are able to make regarding these disparities [in traffic stops with and without citation] are quite limited," and that therefore the events that take place after a stop may be better indicators of racial bias for researchers (Engel 2006).

Distribution of racial identification

It should be noted that 77,258 of the 189,451 records with racial data, or 40%, is listed as "Unknown." If this is equally distributed among races, then excluding it has no effect on the observed bias. However, it is certainly possible that police officers disproportionately place non-black (or multi-ethnic) drivers into the unknown category. For example, by placing Hispanic or other European ethnicities into the unknown category at higher rates than black drivers. Specific training on how to categorize drivers' race could also have a substantial biasing effect on the results. Because the effect could be in either direction (of over- or under-counting bias), I have not adjusted for it in either analysis.

Figure 7: Distribution of Racial identifications in Ferndale citations (U: Unknown, B: Black, W: White, A: Asian, I: Indian)



Veil of Darkness

Making any conclusions from an analysis using the Veil of Darkness method should be done with considerable caution. There are many cases where the assumptions inherent in the Veil method do not apply, as well as confounding factors that may not have been controlled for.

For example, while it may be more difficult for a police officer to see the race of the driver in darkness, it may still be easy to see the make and model of the vehicle, or the state of repair. In many areas, certain classes of vehicles could be disproportionately driven by specific demographics, making the assumption of a true "Veil of Darkness" suspect. Artificial lighting is another unknown factor for Ferndale, MI, that may erode the model's assumptions. It has also been pointed out that assumptions of homogeneity in population samples are unlikely to be true either for time of day or by traffic violations, and that the benchmark sample is still selected for by the police, creating a possibly biased pool of samples (Johnson 2017).

The results from Ferndale should also serve as a warning about overconfidence. Had I stopped at a single analysis of 2016 using only one method, I would not have realized that 2016 just happened to be the largest single outlier from the entire data set. Pursuing a larger data set, and attempting to adjust for age and gender, revealed that the 2016 results are not replicated, and in fact wash out when run across all 7 years together.

Of course, this is not to say that bias definitively does not exist within the Ferndale Police Department according to the Veil. Officers might be dynamically pulling up previous arrest and ticket information about drivers through their in-car license plate terminals, for example, or other biased behavior not picked up by the Veil method. Therefore absence of evidence is not evidence of absence. Instead, what we can say about the Veil method is that it does not show evidence of police bias in the case of Ferndale, MI. I advise caution when applying the method to other data sets, particularly of short duration.

Selection of census tables

The selection of which census tables to use required some compromise. The ideal data set was included within the 2000 census results, which was access to vehicles by household by race. That is, for households of different races, by geographic area, we could determine the relative vehicle access rates. This allows us to interpolate the average household size and age range by race, and arrive at estimates of number of individual adults with access to a vehicle by race. However, at nearly 20 years old, these tables were, I believe, too outdated to be applied to the Ferndale data.

The National Household Transportation Survey, conducted by the Federal Highway Administration (FHWA), also produces vehicle access rates by race. However, these numbers are national, rather than local. And because vehicle access rates differ regionally and between urban and rural settings (Valenzuela, 2000), I believed they were too broad to be used in this application. Likewise, aggregate vehicle available by race in the 2005 American Communities Survey is too old and doesn't include demographic breakdown.

Because of these issues, I chose the MEANS OF TRANSPORTATION TO WORK BY SELECTED CHARACTERISTICS table (S0802) from the 2012-2016 American Community Survey 5-Year Estimates for 5-digit ZIP code tabulation areas (860) within or partially within the state of Michigan. This data provides both vehicle access rates, as well as gender, age, and race percentages, for geographic regions. However, vehicle access rates are for the zip code region, and are not broken down into the other categories of gender, age, and race. That is, the vehicle access rate is for the population as a whole in that zip code.

Therefore, when adjusting for gender, age, and race, the percentages of vehicle access were assumed to be equal between these subgroups. This is likely to overestimate the number of black households with vehicle access, as national data shows that vehicle access rates are on average half for black households than white households (Murakami, 2013). Overestimating the number of black drivers is therefore likely to underestimate the rate of observed bias. In addition, the table uses estimates of the working population, rather than the total population.

This is useful because it approximates the population very likely to be commuting through Ferndale and thus available to be cited by police, but is not an exact representation of all residents with vehicle access. It very likely underrepresents the total population with access to a vehicle, as those with a vehicle but without a job are not counted.

However, there is reason to believe the rate of underestimation is not severe as it might at first seem. The average zip code that drivers with Ferndale citations come from has a racial gap between white and black residents of 81 percentage points, meaning that on average a given area is either 90% black and 10% white, or the reverse. Ferndale itself is 83% white and 7.4% black. In fact, Detroit has the highest percentage of blacks alone-or-in-combination among places with populations of 100,000 or more at 84 percent in the United States (Census 2010). Because there is relatively little racial integration per zip code, the errors in misattribution will be correspondingly small. It is also desirable to be conservative and underestimate rather than overestimate the observed bias, due to the many confounding factors that could account for all or part of the disproportionate rates that black drivers are cited in Ferndale. If we are conservative in our estimates and still find possible bias, we can be more confident in those results.

Factors not adjusted for

Despite making adjustments to the census numbers, there are still several factors that have not been taken into account and should be noted as possible weaknesses of the benchmark. First, racial groups may not be equivalent in the extent of their traffic-law violating behavior. If an ethnic group is more likely to commit violations that result in traffic stops and citations, this may mistakenly appear as bias in my analysis due to the higher number of citations. Second, because the Ferndale police do not record traffic stop without citations, I cannot compare traffic stops with traffic outcomes. It may be that certain ethnic groups are more likely to be stopped but less likely to be cited, or vice versa. Third, there is some evidence to support racial minorities committing offenses at higher rates than white populations (Persico, 2006). However, it may also be that police officers are using minor violations as a “pretext” for disproportionately pulling over minority drivers (Withrow, 2007). Legislating statewide data collection, such as mandated reporting of race in all traffic accidents, would increase confidence by providing additional benchmarks. A statewide mandate to record all traffic stops, whether they result in a citation or not, could also boost public confidence.

Conclusion

In 2014, the ACLU of Michigan raised concerns about police bias after an analysis of Ferndale traffic stop data that compared the rate of minorities receiving tickets to Ferndale demographics (ACLU, 2014). The police department responded critically to the findings, pointing out that the demographics of traffic moving through Ferndale does not necessarily represent those living in Ferndale. But moving forward, a proper traffic demographic study was deemed prohibitively expensive, creating a stalemate between activists and officers.

This preliminary analysis provides incentive to look more closely at officer practices, and conduct a more thorough investigation in the future. While the 40% discrepancy in citations for black drivers highlighted by the ACLU may be an exaggeration, a smaller 29 percentage point discrepancy between black and white drivers found using an adjusted census benchmark, suggests that the ACLU claims should not be dismissed out of hand. Still, considerable caution should be given to making any inferences. Analyzing the complex interactions between citizens and officers is fraught with difficulty, and a variety of interpretations are always possible. As has been mentioned, “the results of benchmark studies can only be described as tenuous” (Vito 2017).

Further study is needed to better understand the extent to which bias may be occurring, possible confounding factors, and possible mitigating actions for the Ferndale Police Department. I appreciate how engaged the Ferndale Police and community have been on this topic, and I hope this preliminary analysis will provide incentive for both activists and the Ferndale Police Department to actively pursue answers and consider possible reforms together.

Future Work

Considerable work still remains to be done. Next steps may include looking at reasons for differences in demographics on major thoroughfares versus local roads (under the assumption that major thoroughfares will contain the majority of pass-through traffic), a more complete graduated analysis looking at the impact of each factor adjusted for, and a full driver demographic study if future grant funding permits.

It may also be very useful to look at possible confounding factors in the citation data. Are minority drivers disproportionately cited for relatively minor offenses? Are there correlations between race and other factors, such as severity of the citation, make and model of vehicle, and previous arrest records?

Looking at specific officer behavior, officer training, and departmental policies would also be useful to determine whether the observed bias is the result of departmental-wide behaviors, or the influence of a smaller number of officers and tactics.

Finally, it could be helpful to study why it is that the Veil of Darkness analysis produced such disparate results between years. Was 2016 merely an outlier, or did departmental practices or staffing change? Because of the high profile of this method in recent years, it would be useful to better understand its limitations in applying it to datasets such as Ferndale's.

Appendix 1

Census benchmark calculations

All									
	YEAR	BLACK_PCT_CITATIONS	BLACK_PCT_CENSUS	WHITE_PCT_CENSUS	WEIGHT_BLACK_PCT_CENSUS	WEIGHT_WHITE_PCT_CENSUS	BLACK_PCT_DIFF	WHITE_PCT_DIFF	BLACK_PVAL
0	(2011, 2011)	0.601756533	0.132914753	0.770807266	0.399327827	0.489343273	0.202428706	-0.091099806	0
0	(2012, 2012)	0.601248487	0.132065313	0.769593655	0.394179028	0.494564823	0.207069459	-0.09581331	0
0	(2013, 2013)	0.573201339	0.131017257	0.773704939	0.378550789	0.510671375	0.194650549	-0.083872714	0
0	(2014, 2014)	0.57288009	0.135137355	0.766652144	0.37916868	0.510500631	0.193711409	-0.083380721	0
0	(2015, 2015)	0.580586398	0.135329109	0.765888563	0.389983153	0.498574636	0.190603246	-0.079161034	0
0	(2016, 2016)	0.575298805	0.14148128	0.756701993	0.388366926	0.499755508	0.186931879	-0.075054313	0
0	(2017, 2017)	0.615720968	0.138587667	0.762275698	0.411609939	0.475892314	0.204111029	-0.091613282	0
0	(2011, 2017)	**0.588529352**	0.114665887	0.792939556	**0.390985371**	0.49772857	**0.197543981**	-0.086257923	0
Adults									
	YEAR	BLACK_PCT_CITATIONS	BLACK_PCT_CENSUS	WHITE_PCT_CENSUS	WEIGHT_BLACK_PCT_CENSUS	WEIGHT_WHITE_PCT_CENSUS	BLACK_PCT_DIFF	WHITE_PCT_DIFF	BLACK_PVAL
0	(2011, 2011)	0.591032252	0.136472746	0.767413341	0.394100775	0.49532672	0.196931477	-0.086358972	0
0	(2012, 2012)	0.58489543	0.135683989	0.766665499	0.385038861	0.504575196	0.199856569	-0.089470626	0
0	(2013, 2013)	0.553238573	0.133403686	0.77221497	0.367561855	0.522792013	0.185676718	-0.076030587	0
0	(2014, 2014)	0.555011338	0.139115236	0.762481525	0.37178032	0.518260885	0.183231018	-0.073272223	0
0	(2015, 2015)	0.561965812	0.14018138	0.761003229	0.381886847	0.507834818	0.180078965	-0.06980063	0
0	(2016, 2016)	0.557956063	0.148000158	0.750957946	0.379450301	0.509065583	0.178505762	-0.067021646	0
0	(2017, 2017)	0.605621595	0.142591178	0.75823556	0.407281299	0.481110568	0.198340296	-0.086732162	0
0	(2011, 2017)	**0.572557737**	0.11616058	0.792399253	**0.383105477**	0.506410448	**0.189452261**	-0.078968185	0
Youth									
	YEAR	BLACK_PCT_CITATIONS	BLACK_PCT_CENSUS	WHITE_PCT_CENSUS	WEIGHT_BLACK_PCT_CENSUS	WEIGHT_WHITE_PCT_CENSUS	BLACK_PCT_DIFF	WHITE_PCT_DIFF	BLACK_PVAL
0	(2011, 2011)	0.651836735	0.172177506	0.718853334	0.423737093	0.461401799	0.228099642	-0.113238534	0
0	(2012, 2012)	0.676945142	0.167886538	0.718343637	0.436487941	0.448227816	0.2404572	-0.125172957	0
0	(2013, 2013)	0.663583815	0.162088505	0.727707717	0.42830377	0.455794546	0.235280045	-0.119378361	0
0	(2014, 2014)	0.656355932	0.160623731	0.726778502	0.41368422	0.474247751	0.242671712	-0.130603683	0
0	(2015, 2015)	0.66097786	0.163040943	0.724534207	0.424937683	0.45859525	0.236040177	-0.119573109	0
0	(2016, 2016)	0.654636313	0.166014739	0.720769168	0.429157637	0.457164887	0.225478676	-0.1118012	0
0	(2017, 2017)	0.662116041	0.171846035	0.713821505	0.43149509	0.451920407	0.230620951	-0.114036448	0
0	(2011, 2017)	**0.661523989**	0.132213115	0.763584891	**0.426998636**	0.458050021	**0.234525352**	-0.11957401	0
Female									
	YEAR	BLACK_PCT_CITATIONS	BLACK_PCT_CENSUS	WHITE_PCT_CENSUS	WEIGHT_BLACK_PCT_CENSUS	WEIGHT_WHITE_PCT_CENSUS	BLACK_PCT_DIFF	WHITE_PCT_DIFF	BLACK_PVAL
0	(2011, 2011)	0.682930583	0.162432561	0.737008434	0.436163672	0.452461137	0.246766911	-0.13539172	0
0	(2012, 2012)	0.695913626	0.162015944	0.735247162	0.434492479	0.45339899	0.261421147	-0.149312616	0
0	(2013, 2013)	0.667676003	0.162050207	0.737128264	0.417862162	0.47066183	0.249813841	-0.138337833	0
0	(2014, 2014)	0.657755776	0.165441371	0.732985436	0.414048647	0.473889396	0.243707128	-0.131645172	0
0	(2015, 2015)	0.666158537	0.1643284	0.733447854	0.428676021	0.458868692	0.237482516	-0.125027229	0
0	(2016, 2016)	0.656140351	0.167094724	0.727761153	0.425279652	0.462677032	0.230860698	-0.118817383	0
0	(2017, 2017)	0.706171735	0.174593095	0.721294195	0.452784569	0.433798658	0.253387166	-0.139970393	0
0	(2011, 2017)	**0.676423721**	0.133646728	0.770368177	**0.429308799**	0.458627131	**0.247114922**	-0.135050852	0
Male									
	YEAR	BLACK_PCT_CITATIONS	BLACK_PCT_CENSUS	WHITE_PCT_CENSUS	WEIGHT_BLACK_PCT_CENSUS	WEIGHT_WHITE_PCT_CENSUS	BLACK_PCT_DIFF	WHITE_PCT_DIFF	BLACK_PVAL
0	(2011, 2011)	0.530430078	0.129170682	0.772819055	0.366960707	0.521751069	0.163469372	-0.052181148	0
0	(2012, 2012)	0.51861131	0.129879689	0.769412736	0.358987723	0.530500208	0.159623587	-0.049111518	0
0	(2013, 2013)	0.492570099	0.127586839	0.774919909	0.344999734	0.5448183	0.147570365	-0.0373884	0
0	(2014, 2014)	0.502662116	0.128693983	0.77297228	0.350312353	0.540789243	0.152349763	-0.043451359	0
0	(2015, 2015)	0.509076433	0.130056314	0.768418411	0.357648731	0.531755654	0.151427703	-0.040832087	0
0	(2016, 2016)	0.508029197	0.139739203	0.75802168	0.357651226	0.53060913	0.150377971	-0.038638327	0
0	(2017, 2017)	0.540283476	0.133182009	0.765944137	0.377269592	0.510999146	0.163013885	-0.051282623	0
0	(2011, 2017)	**0.513877611**	0.108935932	0.798057291	**0.358435951**	0.530938781	**0.155441659**	-0.044816392	0

Appendix 2

Veil of Darkness calculations

All												
EARLY_SUNSET	LATE_SUNSET	ODDS_RATIO	DAY_VEIL_P	DAY_VEIL_STDERROR	BLACK_CNT_DAY	BLACK_CNT_NIGHT	TOTAL_DAY	TOTAL_NIGHT	BLACK_PCT_DAY	BLACK_PCT_NIGHT	TWO_SAMPLE_DIFF	YEAR
16:59:34	21:12:56	1.351319347	0.000542708	0.08704944	1052	418	1734	783	0.606689735	0.533844189	0.000597913	(2011, 2011)
16:59:34	21:12:56	0.926633327	0.332306629	0.078596235	1012	694	1713	1133	0.590776416	0.612533098	0.246262157	(2012, 2012)
16:59:34	21:12:56	1.087433415	0.322143746	0.084661609	932	607	1479	992	0.63015551	0.611895161	0.358601794	(2013, 2013)
16:59:34	21:12:56	0.8169806	0.006646946	0.074479529	1199	739	2105	1189	0.5695962	0.621530698	0.003627091	(2014, 2014)
16:59:34	21:12:56	0.893298164	0.174352816	0.083067624	943	643	1562	1019	0.603713188	0.631010795	0.163685817	(2015, 2015)
16:59:34	21:12:56	1.605847286	3.99E-06	0.102701774	631	455	914	776	0.690371991	0.586340206	8.70E-06	(2016, 2016)
16:59:34	21:12:56	1.03072393	0.776404611	0.106551402	480	516	747	805	0.642570281	0.640993789	0.94839808	(2017, 2017)
16:59:34	21:12:56	1.015763181	0.627652773	0.032245692	6250	4083	10256	6714	**0.609399376**	**0.608132261**	**0.868628552**	(2011, 2017)
Adults												
EARLY_SUNSET	LATE_SUNSET	ODDS_RATIO	DAY_VEIL_P	DAY_VEIL_STDERROR	BLACK_CNT_DAY	BLACK_CNT_NIGHT	TOTAL_DAY	TOTAL_NIGHT	BLACK_PCT_DAY	BLACK_PCT_NIGHT	TWO_SAMPLE_DIFF	YEAR
16:59:34	21:12:56	1.405665624	0.000385629	0.095925912	834	324	1414	640	0.589816124	0.50625	0.000404677	(2011, 2011)
16:59:34	21:12:56	0.930824444	0.409497949	0.086913854	805	532	1411	899	0.570517364	0.591768632	0.313174186	(2012, 2012)
16:59:34	21:12:56	1.077674217	0.430671107	0.094925205	745	464	1201	768	0.620316403	0.604166667	0.472761347	(2013, 2013)
16:59:34	21:12:56	0.828450787	0.023028445	0.082798485	941	579	1687	953	0.557794902	0.607555089	0.012969567	(2014, 2014)
16:59:34	21:12:56	0.833326135	0.047104399	0.091837332	724	507	1260	819	0.574603175	0.619047619	0.043919261	(2015, 2015)
16:59:34	21:12:56	1.640818428	1.47E-05	0.114273159	507	356	741	619	0.684210526	0.575121163	3.18E-05	(2016, 2016)
16:59:34	21:12:56	1.025292322	0.829572194	0.116040566	409	410	647	648	0.632148377	0.632716049	0.983098146	(2017, 2017)
16:59:34	21:12:56	1.012409053	0.729933747	0.035724807	4966	3181	8363	5359	**0.59380605**	**0.593580892**	**0.979097941**	(2011, 2017)
Youth												
EARLY_SUNSET	LATE_SUNSET	ODDS_RATIO	DAY_VEIL_P	DAY_VEIL_STDERROR	BLACK_CNT_DAY	BLACK_CNT_NIGHT	TOTAL_DAY	TOTAL_NIGHT	BLACK_PCT_DAY	BLACK_PCT_NIGHT	TWO_SAMPLE_DIFF	YEAR
16:59:34	21:12:56	1.121827506	0.59059162	0.213686928	218	94	320	143	0.68125	0.657342657	0.612162125	(2011, 2011)
16:59:34	21:12:56	0.973842855	0.888220092	0.188573809	207	162	302	234	0.685430464	0.692307692	0.864613396	(2012, 2012)
16:59:34	21:12:56	1.162035313	0.42708241	0.189088583	187	143	278	224	0.672661871	0.638392857	0.421265863	(2013, 2013)
16:59:34	21:12:56	0.768194024	0.125272546	0.172022591	258	160	418	236	0.61722488	0.677966102	0.120336917	(2014, 2014)
16:59:34	21:12:56	1.244292701	0.272511966	0.199187122	219	136	302	200	0.725165563	0.68	0.276289864	(2015, 2015)
16:59:34	21:12:56	1.459458038	0.111779284	0.237739994	124	99	173	157	0.716763006	0.630573248	0.094824505	(2016, 2016)
16:59:34	21:12:56	1.17584928	0.561127192	0.278732934	71	106	100	157	0.71	0.675159236	0.556445854	(2017, 2017)
16:59:34	21:12:56	1.063347923	0.417866398	0.075818044	1284	902	1893	1355	**0.678288431**	**0.665682657**	**0.450156976**	(2011, 2017)
Female												
EARLY_SUNSET	LATE_SUNSET	ODDS_RATIO	DAY_VEIL_P	DAY_VEIL_STDERROR	BLACK_CNT_DAY	BLACK_CNT_NIGHT	TOTAL_DAY	TOTAL_NIGHT	BLACK_PCT_DAY	BLACK_PCT_NIGHT	TWO_SAMPLE_DIFF	YEAR
16:59:34	21:12:56	1.452366665	0.005017342	0.133002596	586	206	853	342	0.686987104	0.602339181	0.005149708	(2011, 2011)
16:59:34	21:12:56	1.001733229	0.988674345	0.121995014	566	340	832	498	0.680288462	0.682730924	0.926293813	(2012, 2012)
16:59:34	21:12:56	1.191170495	0.185141955	0.132018725	519	297	725	436	0.715862069	0.681192661	0.210658283	(2013, 2013)
16:59:34	21:12:56	0.889209484	0.313642008	0.116535663	669	354	1015	514	0.6591133	0.688715953	0.24520313	(2014, 2014)
16:59:34	21:12:56	0.709383667	0.010089464	0.133459926	497	340	735	456	0.676190476	0.745614035	0.010829681	(2015, 2015)
16:59:34	21:12:56	1.858558882	0.000135569	0.162416813	350	219	453	334	0.772626932	0.655688623	0.000291076	(2016, 2016)
16:59:34	21:12:56	1.00820196	0.962674042	0.174547344	255	264	342	354	0.745614035	0.745762712	0.996407219	(2017, 2017)
16:59:34	21:12:56	1.035857538	0.485310431	0.050487649	3442	2026	4955	2941	**0.694651867**	**0.688881333**	**0.591117244**	(2011, 2017)
Male												
EARLY_SUNSET	LATE_SUNSET	ODDS_RATIO	DAY_VEIL_P	DAY_VEIL_STDERROR	BLACK_CNT_DAY	BLACK_CNT_NIGHT	TOTAL_DAY	TOTAL_NIGHT	BLACK_PCT_DAY	BLACK_PCT_NIGHT	TWO_SAMPLE_DIFF	YEAR
16:59:34	21:12:56	1.216717484	0.094336117	0.117251584	466	212	881	441	0.528944381	0.480725624	0.098169529	(2011, 2011)
16:59:34	21:12:56	0.82747911	0.071248145	0.104979319	446	354	881	635	0.506242906	0.557480315	0.048659818	(2012, 2012)
16:59:34	21:12:56	0.964281797	0.746583768	0.112554608	413	310	754	556	0.547745358	0.557553957	0.724208594	(2013, 2013)
16:59:34	21:12:56	0.720625401	0.000916288	0.098833035	530	385	1090	675	0.486238532	0.57037037	0.000586508	(2014, 2014)
16:59:34	21:12:56	1.015878355	0.886063366	0.109944312	446	303	827	563	0.53929867	0.538188277	0.967480726	(2015, 2015)
16:59:34	21:12:56	1.378725476	0.017666169	0.135365168	281	236	461	442	0.609544469	0.533936652	0.021687563	(2016, 2016)
16:59:34	21:12:56	1.028145369	0.842043285	0.139283863	225	252	405	451	0.555555556	0.558758315	0.92495937	(2017, 2017)
16:59:34	21:12:56	0.951493661	0.246054745	0.042864551	2808	2057	5301	3773	**0.529711375**	**0.545189504**	**0.145070337**	(2011, 2017)

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