# Urbana IDOT Statistics Committee Memo

Prepared for Meeting on September 17, 2014

### Overview

Below are some initial analyses of the IDOT data from 2004-13. Throughout, the data are examined by four racial categories: White (WH), African American (AA), Hispanic (HS), and Asian (AS).

We begin by looking at the frequence of stops by race and type of stop, looking at the total number of the stops, the proportion of stops by race, and the rate of types of stops for each racial group.

Next we examine three possible outcomes of the stop: 1.) Whether a citation was issued 2.) Whether a search was conducted 3.) Whether contraband was found. For each of these outcomes, we look at the frequency of events (e.g. How many citations were issues to Whites in a given year), the distribution of events within racial groups (e.g. what proportion of the total number of citations went to White drivers), and the rate of events within racial groups (e.g. What proportion of White drivers who were stopped got a ticket). The search category includes both searches conducted with consent and probable cause. The contraband category indicates that drugs, drug paraphernalia, alcohol, and/or weapons were found during the stop, and is available from 2006-13

We also examine some additional demographics of the driver. Specifically, we look at racial variation in the residency, gender, age, vehicle age, geographic location, and duration of driver stops.

Finally, we present some initial tests of racial profiling using the veil of darkness methodology proposed by Grogger and Ridgeway (2006)

For each section, we've provided a brief description and initial interpretation of the results. We look forward to your feedback.

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## Race and Type of Stop

### Total Number of Stops



Figure 1: Total Number of Stops by Year and Race

The figure shows the total number of stops by year and type of stop for each racial group.

- Moving violations are the most common reason for stop, followed by equipment violations, and stops for License plates/Registration (L/R)
- Increase in total stops peaks at 2009, driven by rises in the number of equipment and L/R stops.
- $\bullet\,$  Increase from 2011-2013 reflects increase across all type of stops.
- White and African American drivers make up the majority of stops.

# **Proportion of Total Stops**

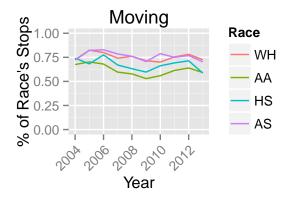


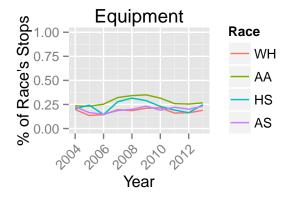
Figure 2: Proportion of Yearly Stops by Race

The figure shows for a given year and type of stop, what proportion of the stops are from what racial group.

- The proportion of total stops by race is relatively constant over the years.
- Whites and African Americans account for generally over 90 percent of all stops
- Whites make up the majority of moving violations
- African Americans account for the plurality of Equipment and L/R stops

## Type of Stop by Race





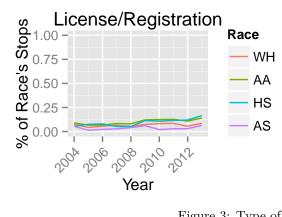


Figure 3: Type of Stop by Race and Year

The figure shows the proportion of each racial group's total stops that are for moving violations, equipment, and L/R.

- Moving violations are the most common type of stop for all races
- Equipment and L/R stops tend to be more common among African Americans and Hispanics

# Citations

### **Total Number of Citations**

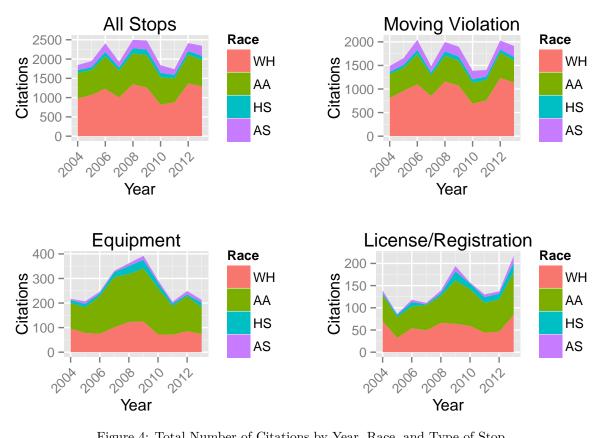


Figure 4: Total Number of Citations by Year, Race, and Type of Stop

The figure shows total number of citations issued in a given year to drivers of a certain race.

# **Propotion of Total Citaitons**



Figure 5: Proportion of Total Citations by Year, Race, and Type of Stop

The figure shows the proportion of total citations in a year issued to each racial group for all stops, and then separately for moving, equipment and L/R violations.

#### Comments

• Gaps between Whites and African American Drivers in terms of citations for Equipment and L/R stops

### **Rates of Citation**

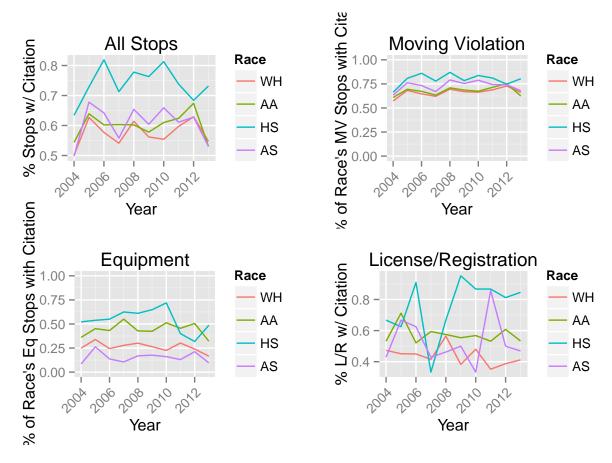


Figure 6: Rates of Citations by Year, Race, and Type of Stop

The figure shows the rates of stops which result in citations for each racial group.

## Comments

• Hispanics are far more likely to get a citation, particularly for L/R stops.

## Searches

### **Total Number of Searches**



Figure 7: Total Number of Searches by Year, Race, and Type of Stop

The figure shows the overall number of stops in year by racial group.

- Overall, it seems the number of searches has been declining.
- The format for reporting searches are reported in the data frequently changed over 2004-2012.

# **Propotion of Total Searches**



Figure 8: Proportion of Total Searches by Year, Race, and Type of Stop

The figure shows for each year what proportion of the years searches were conducted on drivers from each racial group

#### Comments

• African Americans consistently make up the majority of drivers searched.

## **Rates of Searches**



Figure 9: Rates of Searches by Year, Race, and Type of Stop

The figure shows a given racial group, what proportion of their stops result in a search

### Comments

• Hispanic and African American drivers are consistently more likely to be searched during a stop

## Contraband

## Number of Stops with Contraband Found

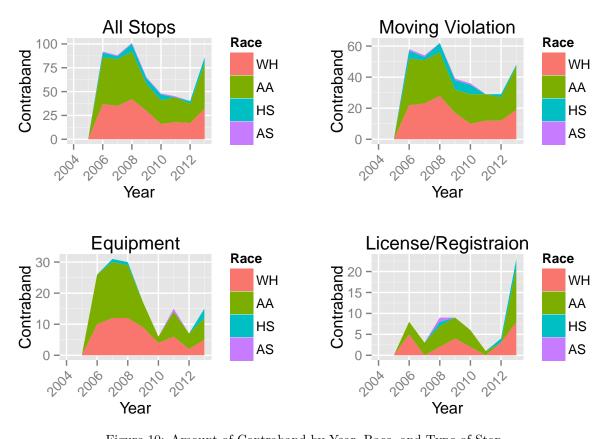


Figure 10: Amount of Contraband by Year, Race, and Type of Stop

The figure shows the total number of stops that resulted in contraband (drugs, paraphernalia, alcohol, weapons) being found.

### \*\* Comments\*\*

- The data start in 2006.
- Finding contraband is a relatively rare experience
- Decline mirrors decline in total number of searches
- A back of the envelop calculation suggests a third of searches produce contraband (will follow up,more formally)

# Proportion of Total Contraband Found

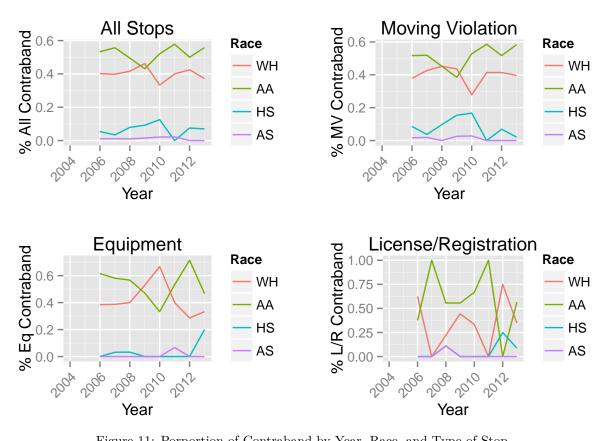


Figure 11: Porportion of Contraband by Year, Race, and Type of Stop

The figure shows the porportion of contraband found by driver's race.

### \*\* Comments\*\*

• Majority of contraband found from stops involving African Americans and Whites

## Proportion of Stops with Contraband Found



Figure 12: Porportion of Stops with Contraband by Year, Race, and Type of Stop

The figure shows the proportion of the stops which result in contraband being found for each racial group.

### Comments

• A relatively small proportion of stops result in contraband being found.

# Other Driver Demographics

## **Driver Residency**

Table 1: Traffic Stops and Driver Residency

Driver From:         # Stops         % Total           Urbana         18974         0.52           Urbana-Champaign         27242         0.75           Local         28384         0.78           Within 50 Miles         30875         0.85           Chicago         505         0.01           Illinois         35425         0.98	Table 1. Italie Stops	and Dilver	recordency
Urbana-Champaign         27242         0.75           Local         28384         0.78           Within 50 Miles         30875         0.85           Chicago         505         0.01	Driver From:	# Stops	% Total
Local         28384         0.78           Within 50 Miles         30875         0.85           Chicago         505         0.01	Urbana	18974	0.52
Within 50 Miles         30875         0.85           Chicago         505         0.01	Urbana-Champaign	27242	0.75
Chicago 505 0.01	Local	28384	0.78
	Within 50 Miles	30875	0.85
Illinois 35425 0.98	Chicago	505	0.01
	Illinois	35425	0.98

Just over half of the drivers stopped from 2004-2013 had addresses in Urbana, IL. Three-quarters lived in Urbana-Champaign (Local includes Savoy and St Jospeh), about 85 percent lived within 50 miles, and close to 98 percent lived in-state.

- What other residency comparisons would you like to see?
  - Broken out by type of stop?

## Gender

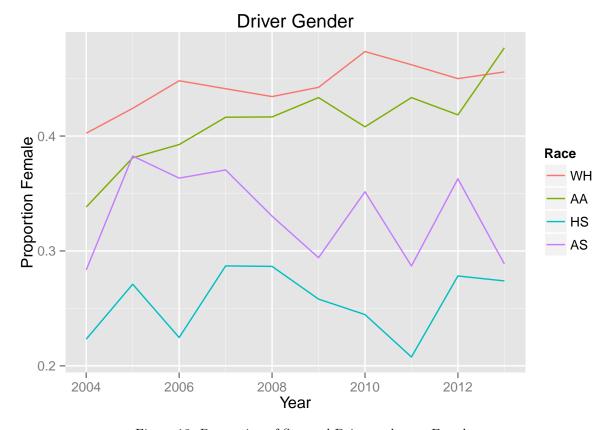


Figure 13: Proportion of Stopped Drivers who are Female

The figure shows the proportion of drivers stopped who are female for each racial group each year. For the most part, men are more likely to be stopped than women, particularly for Asians and Hispanics. Again it would be relatively easy to break this out by type of stop, and also by outcome of stop.

# Driver Age

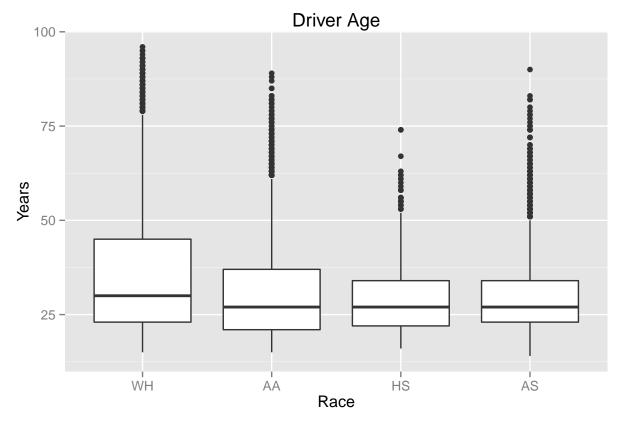


Figure 14: Distribution of Driver's Age by Race

There's greater variation in the age of white drivers, who also on average, tend to be slightly older than minority drivers.

- What other age comparisons would you like to see?
  - Broken out by type of stop?
  - Broken down by outcome of stop

# Vehicle Age

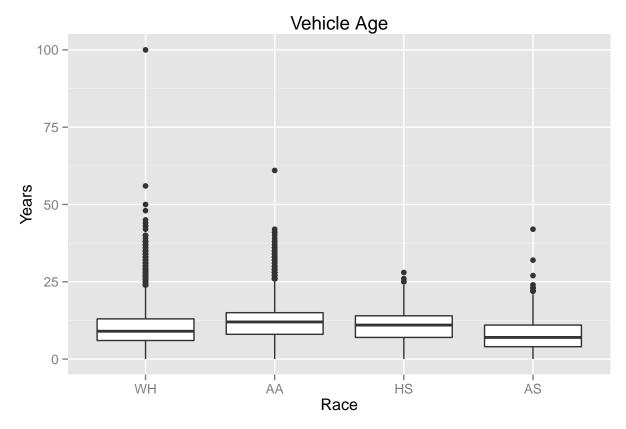


Figure 15: Distribution of Vehicle Age by Race

African Americans and Hispanics tend to drive slightly older cars than Whites and Asians. The hundred-year-old car is likely a 1989 Geo miscoded as a 1909. We'll go through and check to make sure there aren't other outliers.

## Geographic Variation in Stops

This section contains information on geographic variation in traffic stops. The first figure shows the 2014 map of the 5 police beats in Urbana. Each beat is compromised of smaller geocodes, shown in the second figure. There are close to 200 geocodes, some of which report no stops in a given year, others which report over 300. **Note**, the coding appears to change between 2004-06 and 2007-2013, so comparisons, right now can only be made within those years. Next, we provide some context of the racial makeup of these neighborhoods using data from the 2010 census.

The remianing figures show the variation in stops by race for each geocode. In each case, the size of the dot reflects the total number of stops in an area that year, the color shows what proporition of those total stops were minorities or from a specific ethnic group. When looking at rates among specific ethnic groups, the top panel shows the results for all geo-codes and the bottom panel shows geocodes with more than 50 stops, with grey lines connecting the same geocode across the years.

# 2014 Beat Map

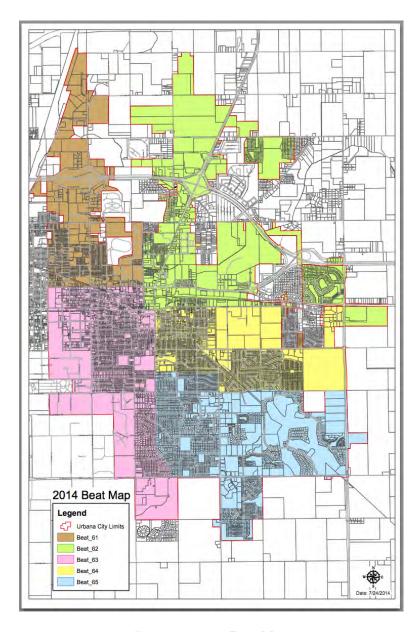


Figure 16: 2014 Beat Map

# 2014 Geo Codes

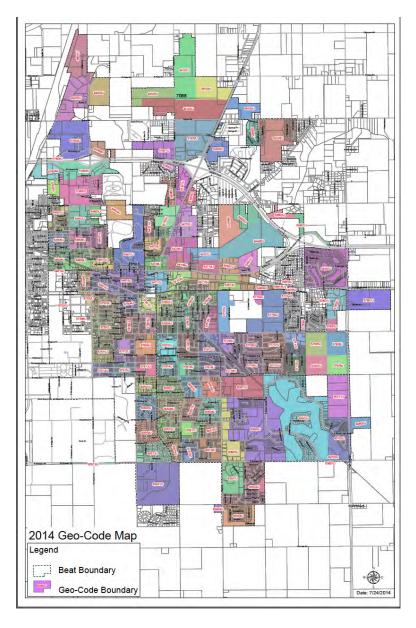


Figure 17: 2014 Geo Codes

# 2010 Cenus Data

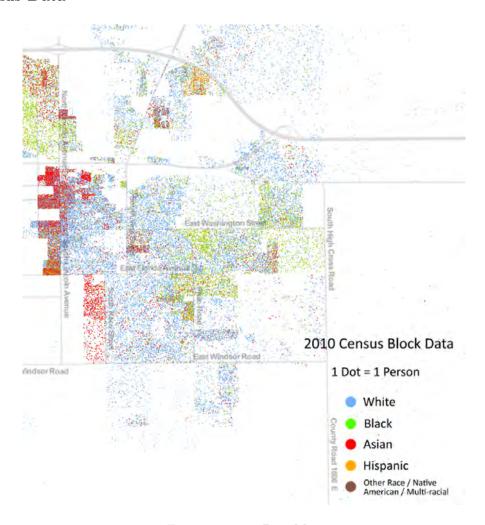


Figure 18: 2014 Beat Map

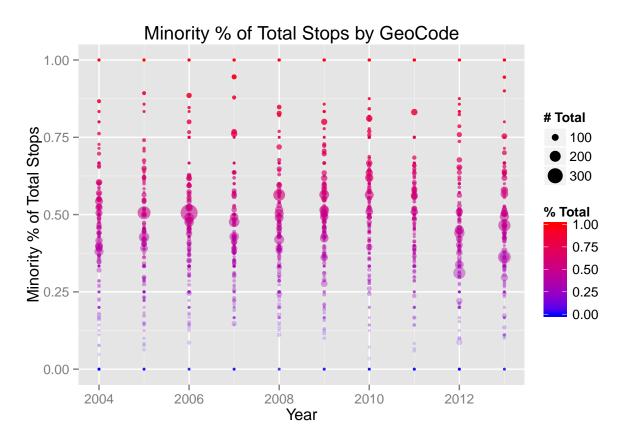
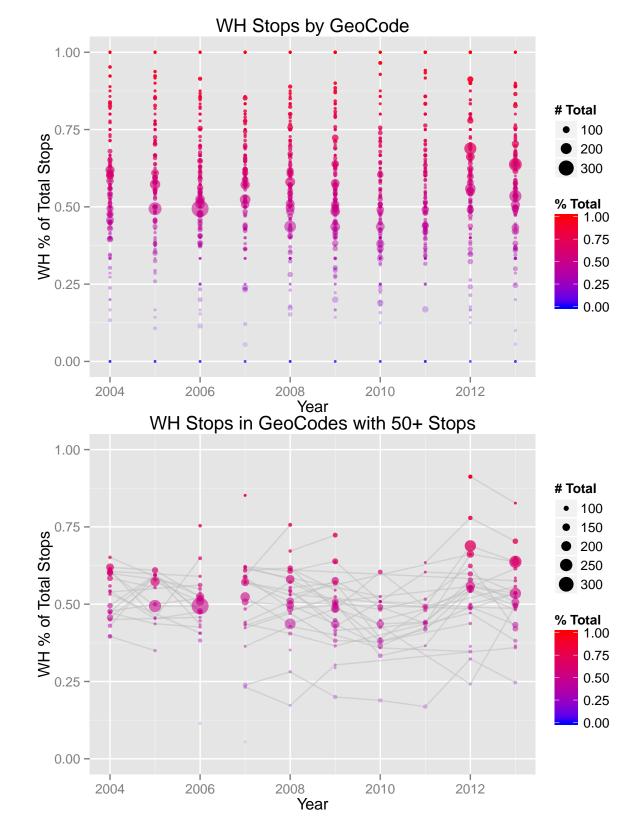
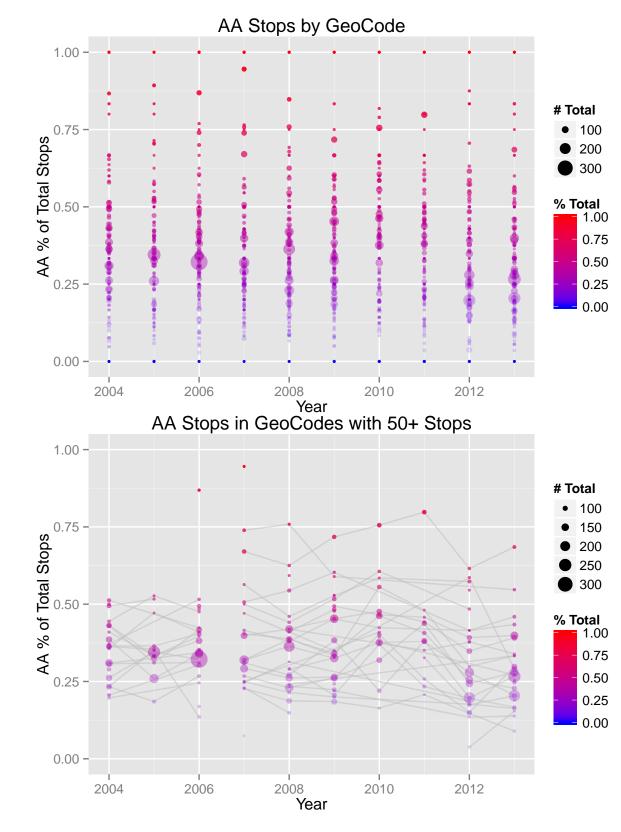


Figure 19: Geographic Variation in Minority Stops

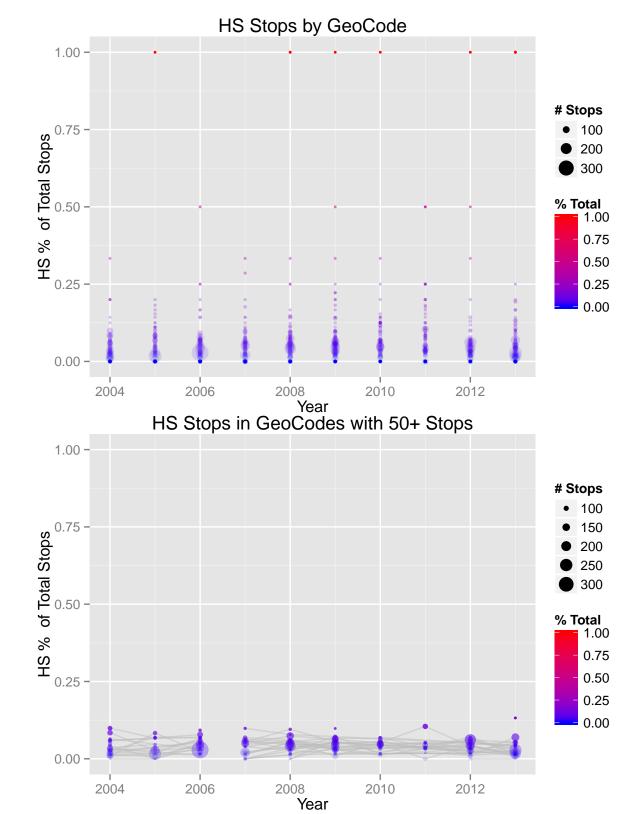
# Geographic Variation: Whites



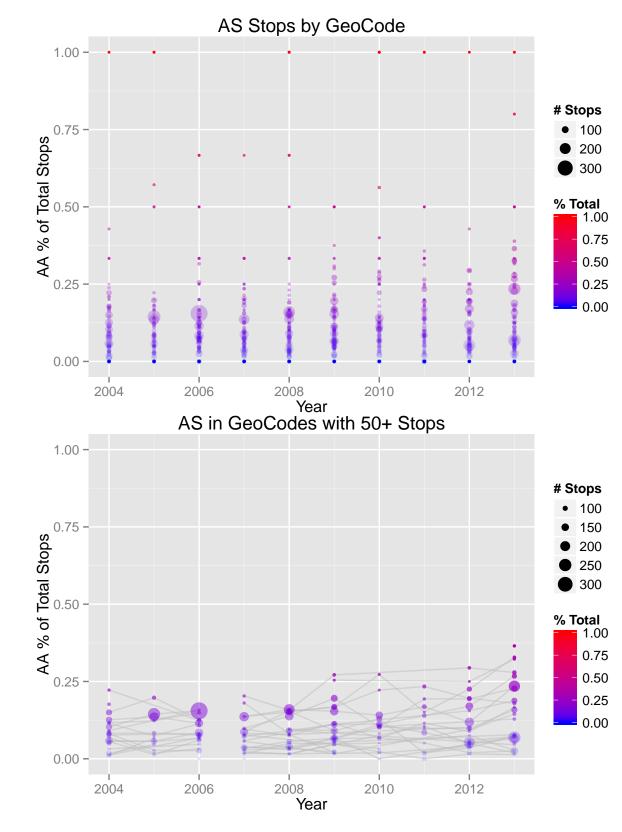
# Geographic Variation: African Americans



# Geographic Variation: Hispanics



# Geographic Variation: Asian



# **Duration of Stops**

The figures below show the average duration of stops and different quantiles (e.g. at the 50th percentile, 50 percent of the drivers have a duration time lower and 50 percent have duration time higher than this value) stop duration for each racial group. The duration of stops tends to be signficantly higher for African Americans and Hispanics.

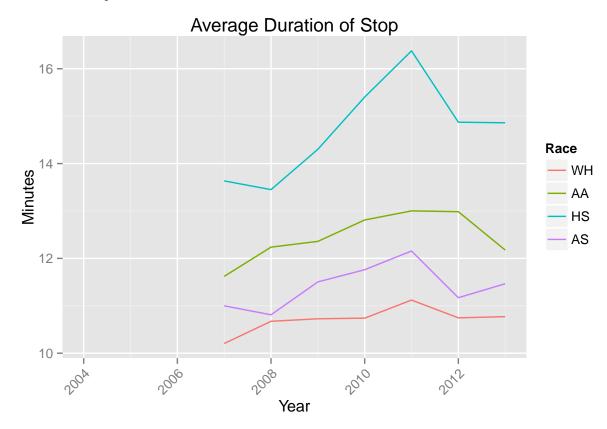


Figure 20: Average Duration of Stops

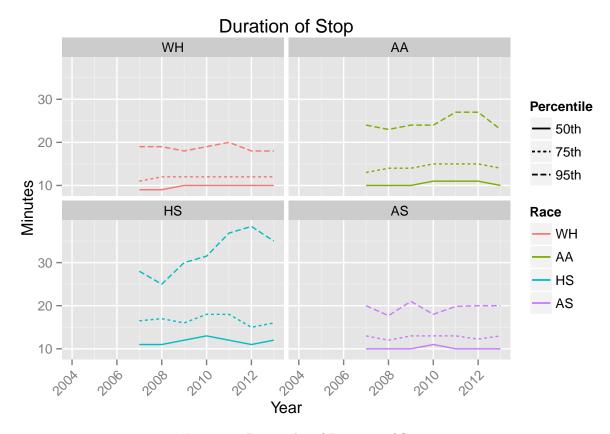


Figure 21: Percentiles of Duration of Stops

# Variation in Stops by Officer

This section shows variation in the rates of minority stops by officers. There are 99 total officers in the data, some of which are present only for some years. The first figure shows minority stops as a proportion of an officer's total stops. Larger dots reflect officers who make more stops, dots which are closer to red reflect officers that stop a higher proportion of minorities.

The next four figures look at each racial group separately. Again, the color of the dot refelcts the proportion of an officer's stops who were from that racial group and size reflects the total number of stops made by an officer. Additionally the grey lines connect the same officer from year to year.

The proportion of Asians and Hispanics stoped is relatively small and constant. Most of the variation comes in the rates at which Whites and African Americans are stopped.

# Officer Variation: Mintority Stops

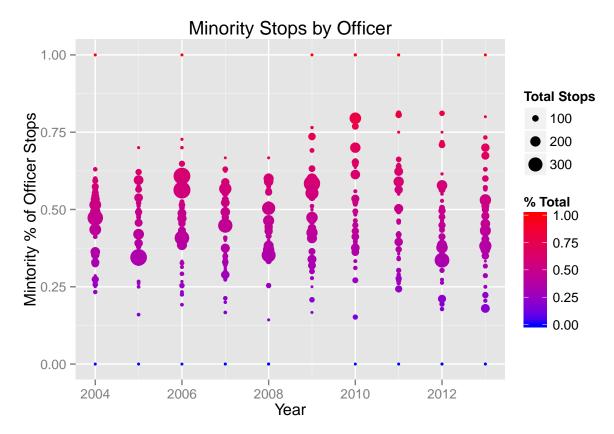


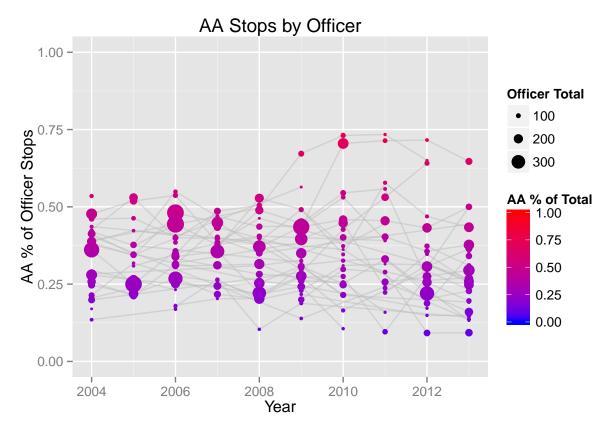
Figure 22: Variation in White Stops by Officer

# Geographic Variation: Whites



Figure 23: Variation in White Stops by Officer

# Geographic Variation: African Americans



# Geographic Variation: Hispanics

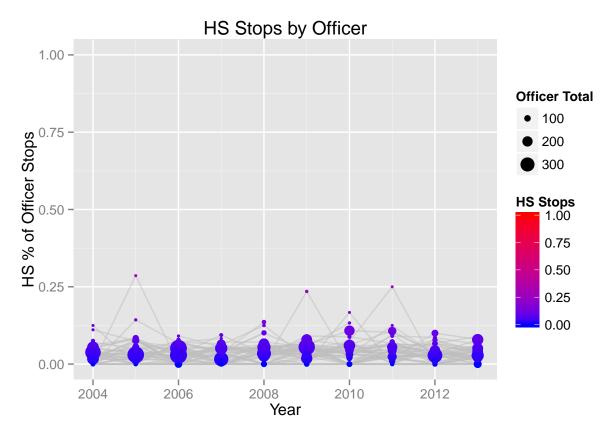


Figure 24: Variation in Hispanic Stops by Officer

# Geographic Variation: Asian

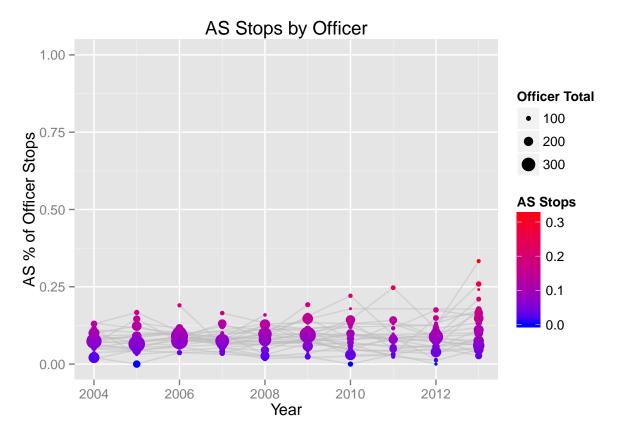


Figure 25: Variation in Asian Stops by Officer

## Testing for Racial Profing Using the Veil of Darkness

Overall, it seems like we are interested in two main questions:

- Do disparties exist in the rates at which minorities are stopped and the outcomes of those stops?
- Why do these disparities exists, and are they the product of racial profiling by the police?

In terms of the first question, the IDOT ratios provide provide a baseline that suggests that minorities are more likely to be stopped than whites given their estimated relative proportion of the driving population. The descriptive statistics presented above provide further insights into the nature of these disparities and even offer some possible causes for why these patterns should exist (e.g. differences in the demographics of the underlying driving population). The real difficulty though, with answering why these disparities exist is that there are any number of possible explanations, some of which we can observe, and some of which we can't. Only controlling for what we observe can't really tell us what we want to know and may even mislead us, if we've left out or can't observe other important factors.

### The Basic Idea

One clever solution proposed by economists is to essentially reframe the problem (Grogger and Ridgeway 2006), and test for for whether racial profiling is occurring by taking advantage of a so-called "veil of darkness". The basic idea is that you can't racially profile drivers if you can't see their race, and it's harder to see a driver's race when it's dark out than when it's light out.

Just comparing the relative rates at which minorities are stopped during the day to the rates at which they are stopped at night doesn't quite tell us what we want to know for a number of reasons (e.g. different groups of people are more or less likely to drive at night; policing patterns vary by time of day, etc.). Instead, the veil of darkness approach makes use of the fact that at different times of the year it can be on either light or dark. You could be driving at 7 p.m. and in the winter it may be dark while in the summer it's light out. In theory whether it's light are dark out should have no effect on whether you get pulled over. You either used your turn signal or you didn't. But if racial profiling is occurring, then the probability that someone pulled over at 7 pm when it's dark out is a minority will be lower than the probability that someone pulled over at 7 pm is a minority when it's light out. So by looking at traffic stops that occur only during the interwlight period (when it could be either light or dark out depending on the time of year) we create a sort of natural experiment that, with some caveats, provides a strong test of whether racial profiling is occurring.

#### Data and Models

- The first set of figure shows the whole dataset, and the subset of stops which occur within the intertwilight period
- The second set of figure 4 shows the breakdown by racial group (In descending order of frequency: Whites, African Americans, Asians, and Hispanics)
- The tables report results from logistic regressions that model the probability that a person stopped is minority (1 if minority, 0 if Caucasian) as a function of whether it was light or dark out. In some cases we let the probability of racial profiling also vary by the time of day within the intertwilight period and the year in which the data were collected.
- The third set of figures provides estimates of the incidence of racial profiling for the most complex/flexible form of our logistic regressions which allow the effect of darkness to vary by time and year.

#### Traffic stops by time of day

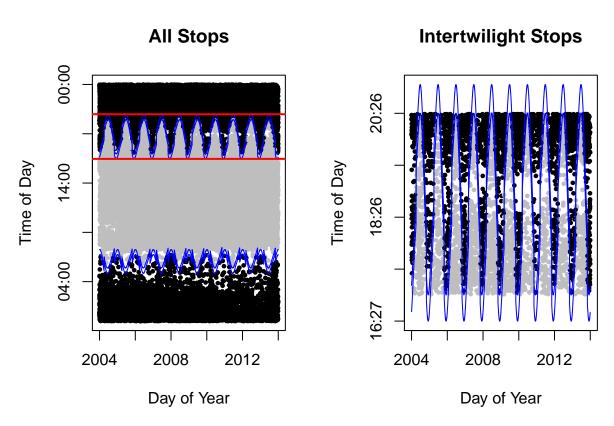


Figure 26: **Traffic Stops by Time of Day:** Grey dots show stops that occurred during the day and black dots show stops that occurred at night. Blue lines show dawn, sunrise, sunset, dusk. Red lines (left panel) denote the intertwilight period (right panel) used in the veil of darkness analysis

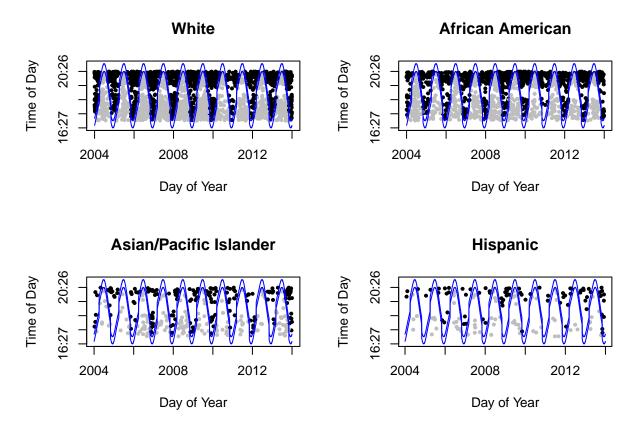


Figure 27: **Intertwighlight traffic stops by race:** The figure shows the breakdown of traffic stops by race for the intertwighlight period between 4:57 pm and 8:26pm Black dots show stops that occur at night.

# Regression Models

	No Time of Day	Linear Effect	Cubic Spline	Interaction	Year FE
Dark Out	0.12*	-0.13	-0.12	-0.97	-0.93
	(0.06)	(0.07)	(0.07)	(0.51)	(0.51)
Time of Day		0.00***			
		(0.00)			
Spline(Time of Day) 1			0.27	0.19	0.19
a. i. (m. a. a. a. a.			(0.21)	(0.25)	(0.25)
Spline(Time of Day) 2			0.74*	0.42	0.42
G 1: (T): (F) ) 9			(0.34)	(0.45)	(0.45)
Spline(Time of Day) 3			0.88***	1.12***	1.12***
Galia (Missa of Dan) A			(0.22) $0.78***$	(0.31) $0.32$	(0.31)
Spline(Time of Day) 4			(0.18)	(0.34)	0.35 $(0.34)$
Spline(Time of Day) 5			1.30**	0.98	0.96
Spline (Time of Day) 5			(0.40)	(0.51)	(0.51)
Spline(Time of Day) 6			0.54**	0.63	0.56
Spinic(Time of Day)			(0.17)	(0.48)	(0.49)
Time of Day X Spline(Time of Day) 1			(0)	0.72	0.67
1 ( )				(0.53)	(0.53)
Time of Day X Spline(Time of Day) 2				1.20	1.22
• • • • • • • • • • • • • • • • • • • •				(0.81)	(0.81)
Time of Day X Spline(Time of Day) 3				0.30	0.25
				(0.58)	(0.58)
Time of Day X Spline(Time of Day) 4				1.05*	0.98*
				(0.50)	(0.50)
Time of Day X Spline(Time of Day) 5				1.90	1.90
				(1.16)	(1.16)
Time of Day X Spline(Time of Day) 6				0.01	0.08
				(0.53)	(0.54)
AIC	5991.48	5940.06	5945.93	5951.22	5948.63
BIC	6004.24	5959.19	5996.95	6040.52	6095.33
Log Likelihood	-2993.74	-2967.03	-2964.96	-2961.61	-2951.32
Deviance Norman also	5987.48	5934.06	5929.93	5923.22	5902.63
Num. obs.	4351	4351	4351	4351	4351

\*\*\*p < 0.001, \*\*p < 0.01, \*p < 0.05

Table 2: Testing for Racial Profiling of Minorities

	No Time of Day	Linear Effect	Cubic Spline	Interaction	Year FE
Dark Out	0.15*	-0.13	-0.12	-1.06	-0.98
	(0.07)	(0.08)	(0.08)	(0.56)	(0.56)
Time of Day		0.00***			
G 1: (F) 1		(0.00)	0.07	0.00	0.01
Spline(Time of Day) 1			0.07	0.00	0.01
Spline(Time of Day) 2			$(0.23) \\ 0.81^*$	$(0.28) \\ 0.46$	$(0.28) \\ 0.38$
Spline(Time of Day) 2			(0.37)	(0.49)	(0.49)
Spline(Time of Day) 3			0.92***	1.23***	1.27***
Spinie(Time of Bay) o			(0.24)	(0.33)	(0.33)
Spline(Time of Day) 4			0.76***	0.19	0.18
((			(0.20)	(0.37)	(0.37)
Spline(Time of Day) 5			1.18**	0.70	0.66
			(0.44)	(0.56)	(0.56)
Spline(Time of Day) 6			0.58**	0.62	0.57
			(0.18)	(0.52)	(0.52)
Time of Day X Spline(Time of Day) 1				0.74	0.61
				(0.59)	(0.59)
Time of Day X Spline(Time of Day) 2				1.27	1.33
T: (D V(I) (T: (D ))				(0.89)	(0.89)
Time of Day X Spline(Time of Day) 3				0.25	0.14
T:(D. V.C.):(T:(D. ) 4				$(0.64) \\ 1.23^*$	$(0.64) \\ 1.14^*$
Time of Day X Spline(Time of Day) 4				(0.54)	(0.54)
Time of Day X Spline(Time of Day) 5				2.29	2.24
				(1.29)	(1.29)
Time of Day X Spline(Time of Day) 6				0.03	0.05
				(0.57)	(0.57)
AIC	5123.67	5066.12	5069.45	5072.35	5065.71
BIC	5136.18	5084.89	5119.51	5159.95	5209.63
Log Likelihood	-2559.83	-2530.06	-2526.73	-2522.18	-2509.86
Deviance	5119.67	5060.12	5053.45	5044.35	5019.71
Num. obs.  *** n < 0.001 ** n < 0.01 * n < 0.05	3855	3855	3855	3855	3855

p < 0.001, p < 0.01, p < 0.05

Table 3: Testing for Racial Profiling of African Americans

# Yearly Estimates of Racial Profiling with Log-Odds

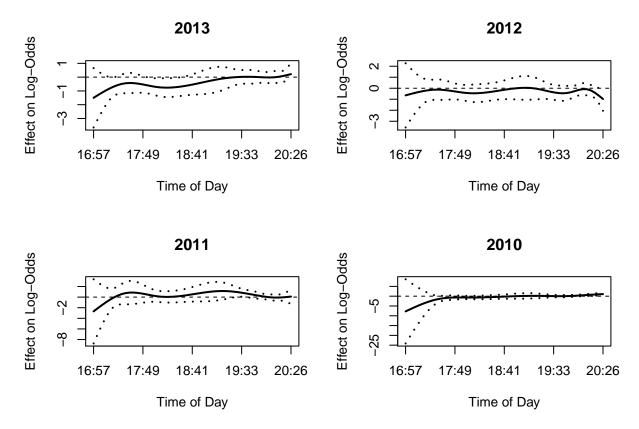
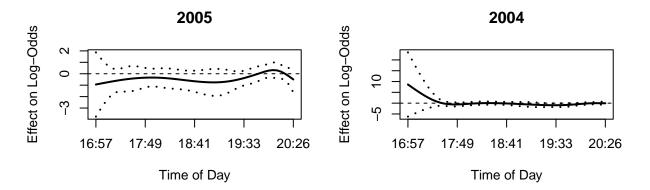


Figure 28: Yearly Estimates of Racial Profiling of Minorities (2000-13)



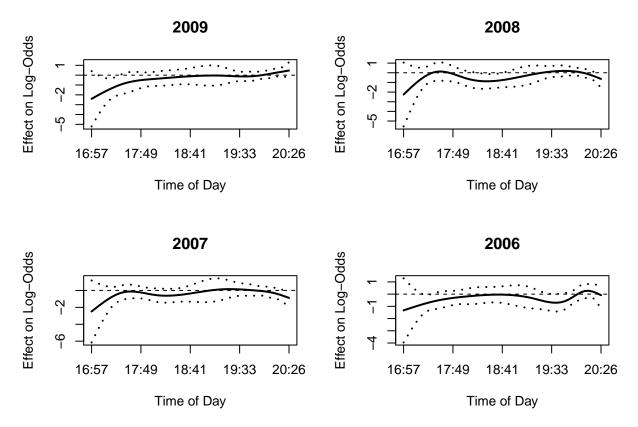


Figure 29: Yearly Estimates of Racial Profiling of Minorities (2006-09)

#### Interreting the Tables

- The first column of results in each table are from a model predicting the probability that a person stopped was a minority with only one variable: an inidcator for wheter it was light or dark out when they were stopped. If the coefficient is negative, this provides evidence of racial profiling (Being dark out decreases the probability that a person stopped is a minority). If the standard error (the number in parantheses) is small relative to this coefficient then this gives us a sense of how likely is it that relationships we see occured by chance. If it's very unlikley (small standard errors relative to coefficients) then we say the estimates are statistically significant
  - The first columns present results estimating the effect of darkness conditional on what time of day a person was stopped.
  - The second column lets the effet of the time of day at which a person was stopped vary linearly (i.e. as the time of day gets later, the probability that a person stopped is a minority can either go up or down.).
  - The third column uses a cubic spline to let the effects of time of day vary over time.
  - The fourth column lets the effects of darkness vary along with time of day.
  - The fifth column adds "fixed effects" to control for yearly variation.
  - Finally, we estimate but do not report in this table, models in which the effect of darkness is allowed to vary both by time of day and year. These models are equivalent to estimating the models in fourth column separately for each year. Instead of reporting all the coefficients from this model, we instead plot the effect for each year from 2004 to 2013.
- The benefit of the first model is that it's relatively easy to interpret. The tradeoffs with the other models is that they're more flexible but harder to interpret. In short, their is no longer a single effect of darkness to test. Rather the effects of darkness are condtional on a what time of day and some cases,

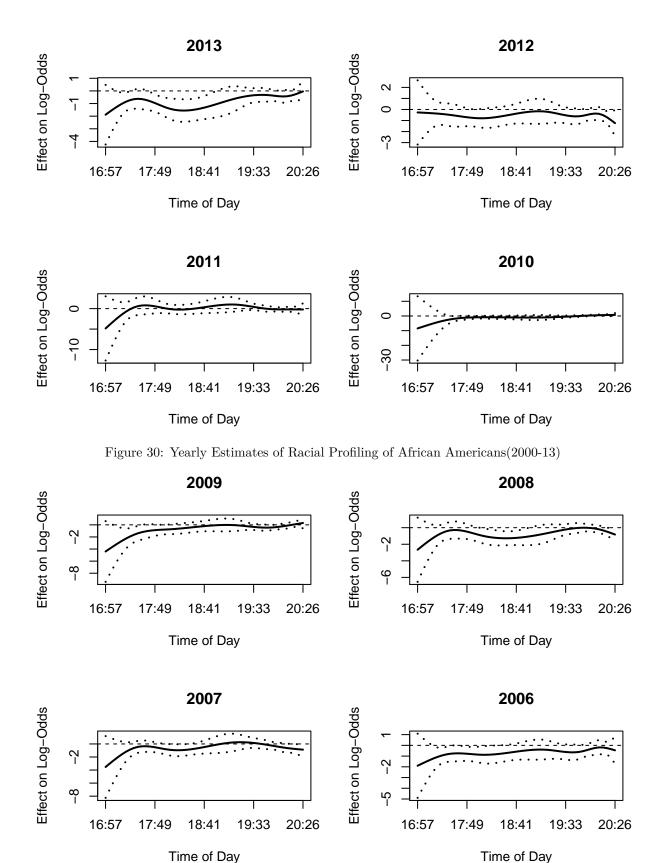


Figure 31: Yearly Estimates of Racial Profiling of African Americans (2006-09)

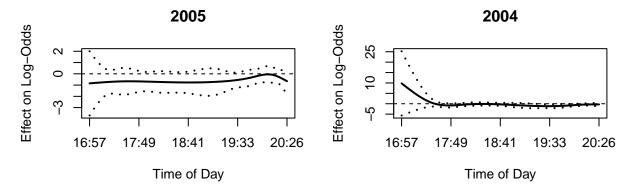


Figure 32: Yearly Estimates of Racial Profiling of African Americans (2004-06)

what year it is.

#### Intereting the Figures

• The solid black lines in Figure X shows how the effects of darkness vary over the time of day for the the fourth models from Table 2 (All Minorities) and Table 3 (African Americans). In this case, it's easier to look at the uppler and lower confidence intervals shown by the dotted lines (another way of assessing the statistical significance of an estimate) and ask do they include zero. If they do, then we're not confident in our results (the true value could be either positive or negative). If they're don't and if our estimate is negative, then this provides evidence of racial profiling.

#### **Summary**

- Ok, so do the data provide evidence of racial profilining?
- The short answer is that the results are mixed and depend on if and how we condition for the time of day and the year.
  - None of the simple estimates for the presence of racial profiling are statistically signficant.
  - When we condition the effects of darkness on the time of day and year of the stop, the effects of darkness for the all minority model are generally negative, but statistically insignificant, while the effects for African Americans appear to be negative and statitically significant for the period between 5 and 6:30. (Practically, we're talking about an increased probability of about 2-3 percentage points during the day)
- If we believed that there was systeme, institutionalized racial profiling occurring, we'd expect that the specification wouldn't matter. The fact that it does and the results are so mixed, probably suggests that extreme is not the case.
  - Another way of interpreting these data would be to look at the effect of darkness on the predicted probability that a driver stopped is minority or African American. We'll have something more formall, but the overall the overall effects tend to be a few percentage points, smaller than results found in other cities where there was clear, consistent evidence of racial profiling.
- However, failure to reject the null hypothesis of no racial profiling does not mean we accept it as true. There simply isn't enough evidence in our data to consistently reject it. However, the fact that under some specifications and conditions the estimates do point towards some racial profiling, probably means there's something there. What that something is (e.g. traffic stops being used for investigative tools/community policing) probably requires both more qualitative t and quantitative assessments on our part.

#### **Further Analysis**

Here are some brief directions for further analysis we might pursue. We look forward to your input and recommendation

- Spatial analysis/descripton, adding crime and other contextual data
- Further veil of darkness analyses
  - Specification tests
  - Separate by Type of stop
  - Separate estimates for Hispanics, Asians (Hard to control for time of day)
- Conditional analysis of differences in outcomes (e.g. controlling for differences in the type of stop, age of driver, etc, do we still observe differences in race)
- Further analysis of moving violations by type of moving violation (six categories)
- Detailed discussion of IDOT Methodology and it's limitations.
- Comparison to other communities, similar communities.

# **Appendix**

We'll provide tables with the raw counts and proportions depicted in the figures above before the meeting. For now, here are some other tables



Figure 33: tables

# References

Grogger, Jeffrey, and Greg Ridgeway. 2006. "Testing for Racial Profiling in Traffic Stops from Behind a Veil of Darkness." Journal of the American Statistical Association 101 (475). Taylor & Francis: 878–87.

# Urbana Traffic Stop Data Task Force Statistics Subcommittee: Initial Findings

#### Paul Testa

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September 17, 2014

#### Overview

Data on 36,258 stops from 2004-2013

- Race and Type of Stop
- Race and Outcome of Stop
- Race and Demographics
- Additional Analysis
- Tests for Racial Profiling

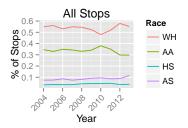
# Type of Stop

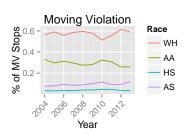
- Three Types of Stop: Moving Violation (MV), Equipment (Eq) and License Plate/Registration (L/R)
- Frequency: Total number of stops each year by race
- Proportion: Proportion of stops accounted for by each race
- Percentage: What percent of race's stops were for what type of violation

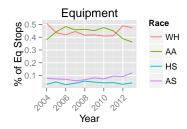
# Type of Stop: Frequency

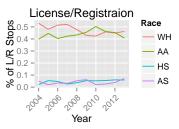


# Type of Stop: Proportion of Total

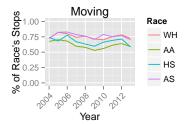


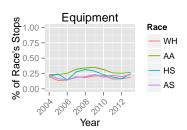


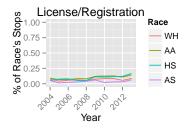




# Type of Stop: Percentages by Race







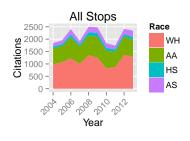
### Type of Stop: Summary

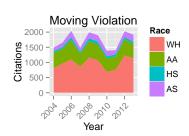
- Moving violations are most common
- African Americans pulled over more often, particularly for Eq and L/R stops

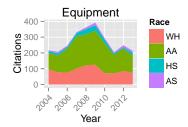
#### Outcome of Stop

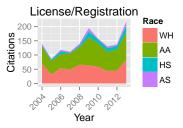
- Three Outcomes: Citations, Searches, Contraband
- Citations: Citation or Written Warning
- Search: Both Consent and Probable Cause
- Contraband: Were drugs, paraphernalia, alcohol, or weapons

#### Citations: Frequency

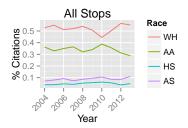


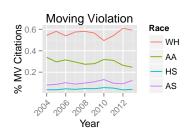


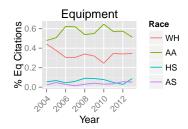


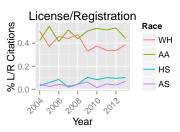


# Citations: Proportion of Total

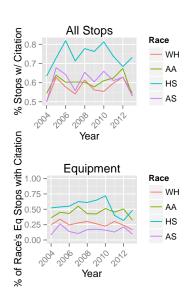


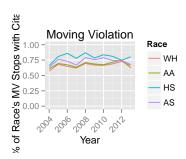


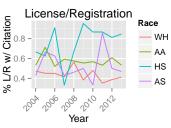




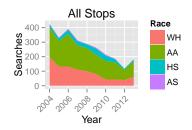
#### Citations: Percentages by Race

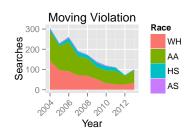


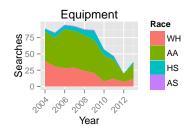


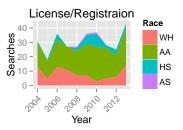


#### Searches: Frequency

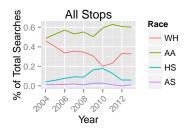


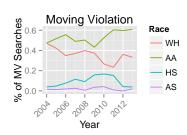


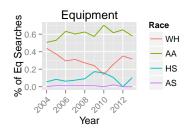


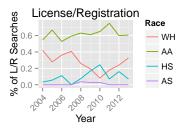


#### Searches: Proportion of Total

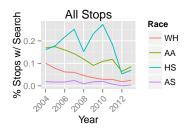


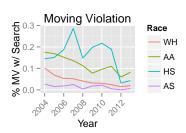


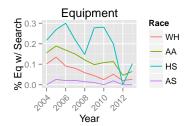


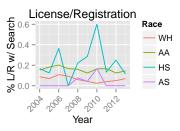


# Searches: Percentages by Race



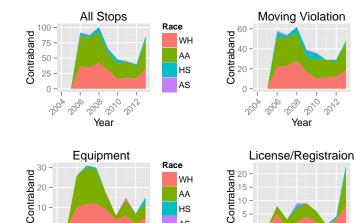






# Contraband: Frequency

Year



AS



Race

Race

WH

AΑ

HS

AS

WH

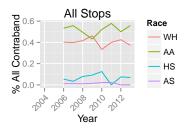
AA

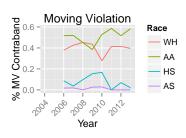
HS

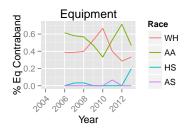
AS

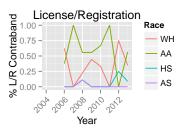
Year

# Contraband: Proportion of Total

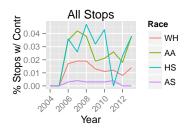


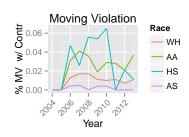


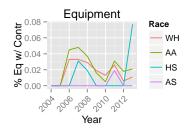


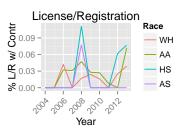


# Contraband: Percentages by Race









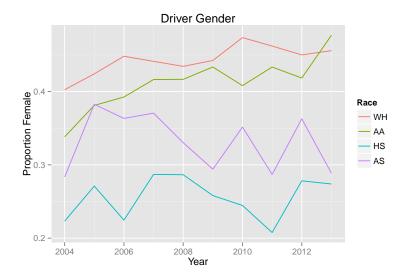
# Outcome of Stop: Summary

- Citations: Minorities more likely to get a ticket, particularly Hispanics
- Searches: Overall declined over time, Hispanics and African Americans more likely to be searched
- Contraband: Small of stops with contraband, more likely to be found during stops of African American and Hispanic drivers.
- These relationships remain in multivariate regressions, controlling for characteristics of the driver, officer, location of stop, and year.

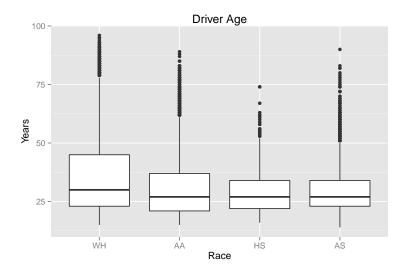
#### **Demographics**

- Gender: Proportion of Drivers stopped who are female by race
- Driver Age: Distribution of Driver Age by race
- Vehicle Age: Distribution of Driver Age by race
- Driver Residency: Urbana, U-C, Local, Regional, State, Chicago

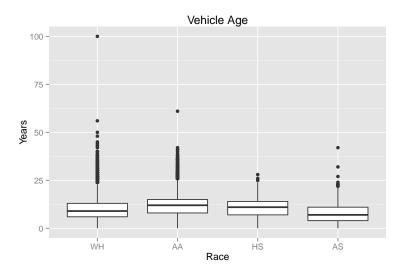
# Demographics: Female Drivers



# Demographics: Driver Age



# Demographics: Vehicle Age



# Demographics: Residency

Table: Traffic Stops and Driver Residency

Driver From:	# Stops	% Total	
Urbana	18974	0.52	
Urbana-Champaign	27242	0.75	
Local	28384	0.78	
Within 50 Miles	30875	0.85	
Chicago	505	0.01	
Illinois	35425	0.98	

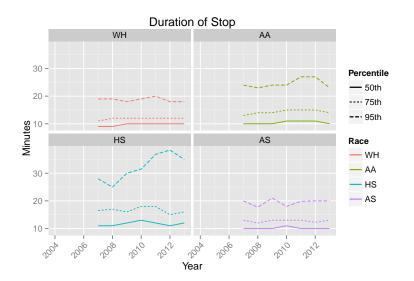
## Demographics: Summary

- Gender: Large differences in the rates at which female drivers are stopped
- Driver Age: Minorities are on average younger than white drivers
- Vehicle Age: AA and HS drive slightly older cars
- Driver Residency: 75 percent of stops from U-C region.

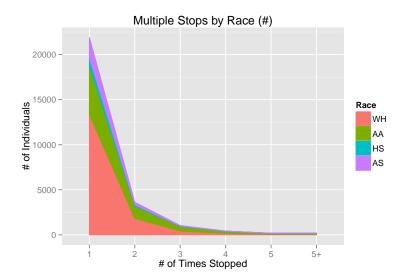
#### Additional Analyses

- Duration of Stops
- Multiple Stops of the Same Person
- Geographic Variation
- Variation by Officer

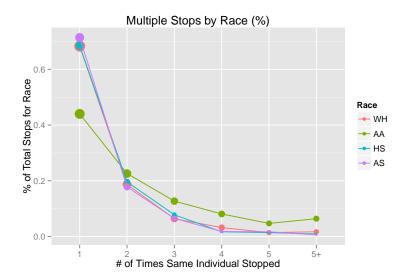
### **Duration of Stop**



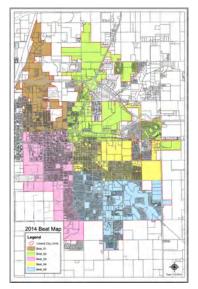
### Multiple Stops: Frequency



#### Multiple Stops: Percentage



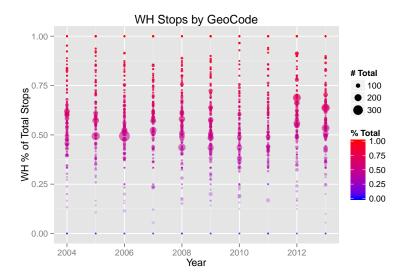
# Geographic Variation: Beat Maps



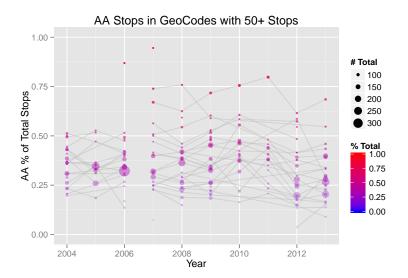
# Geographic Variation: Geo Codes



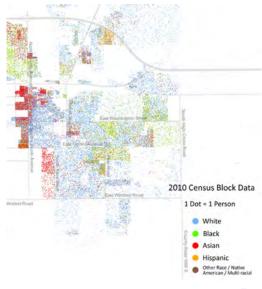
## Geographic Variation by Geo Code



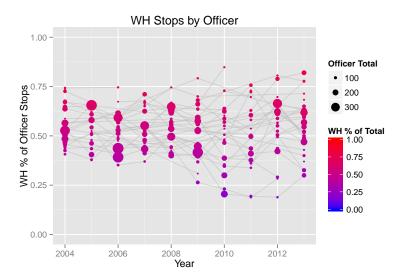
#### Geographic Variation by Geo Code



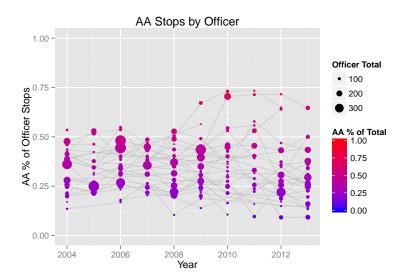
## Geographic Variation: What's the Baseline?



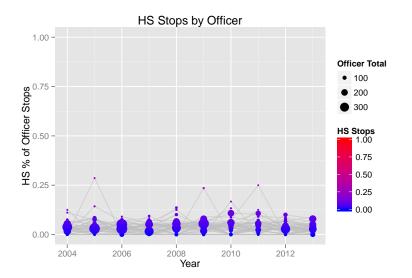
## Variation by Officer: Whites



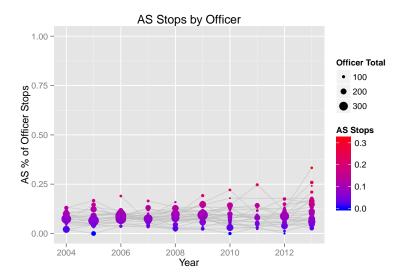
#### Variation by Officer: African Americans



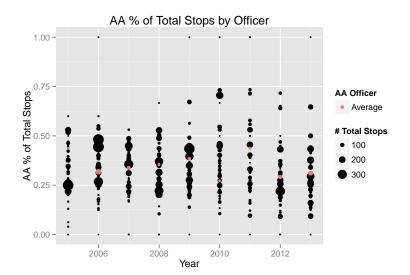
## Variation by Officer: Hispanics



### Variation by Officer: Asians



## Comparing Stops by AA and WH Officers



#### Additional Analyses

- Duration: Much longer among HS
- Multiple Stops: More frequent among AA
- Geographic Variation: Lots of it, primarily in rates of WH and AA stops
- Variation by Officer: Similar to geographic. Black officers tend to be near center of distribution

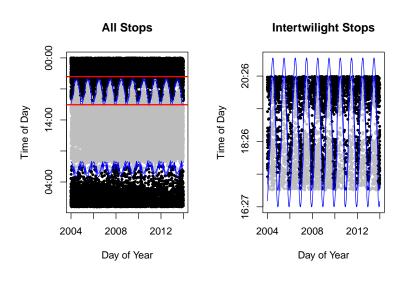
#### Tests of Racial Profiling

#### The "Veil of Darkness"

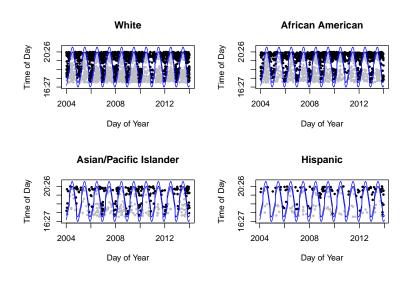
- If profiling is occurring it should be harder to profile when its dark out
- There are times of the year when it can be either light or dark out
- This creates a natural experiment where in theory the only thing that varies is whether it's light or our dark.
- If minorities are less likely to be stopped when it's dark out, this provides evidence of racial profiling.
- Complications: How to control for remaining differences across time of day and years?



### Stops and Time of Day



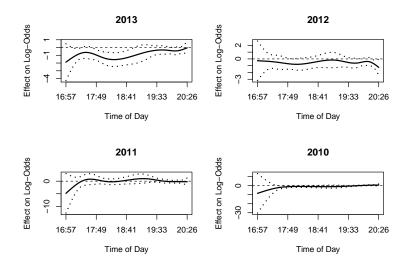
## Stops and Time of Day



	No Time of Day	Linear Effect	Cubic Spline	Interaction	Year FE
Dark Out	0.15*	-0.13	-0.12	-1.06	-0.98
	(0.07)	(0.08)	(80.0)	(0.56)	(0.56)
Time of Day		0.00***			
		(0.00)			
Spline(Time of Day) 1			0.07 (0.23)	0.00 (0.28)	0.01 (0.28)
Spline(Time of Day) 2			0.23)	0.46	0.38
			(0.37)	(0.49)	(0.49)
Spline(Time of Day) 3			0.92***	1.23***	1.27***
			(0.24)	(0.33)	(0.33)
Spline(Time of Day) 4			0.76***	0.19	0.18
(			(0.20)	(0.37)	(0.37)
Spline(Time of Day) 5			1.18**	0.70	0.66
			(0.44)	(0.56)	(0.56)
Spline(Time of Day) 6			0.58**	0.62	0.57
Time of Day X Spline(Time of Day) 1			(0.18)	(0.52)	(0.52)
				0.74	0.61
				(0.59)	(0.59)
Time of Day X Spline(Time of Day) 2				1.27 (0.89)	1.33 (0.89)
Time of Day X Spline(Time of Day) 3				0.25	0.14
Time of Day A Spline(Time of Day) 3				(0.64)	(0.64)
Time of Day X Spline(Time of Day) 4				1.23*	1.14*
				(0.54)	(0.54)
Time of Day X Spline(Time of Day) 5				2.29	2.24
				(1.29)	(1.29)
Time of Day X Spline(Time of Day) 6				0.03	0.05
				(0.57)	(0.57)
AIC	5123.67	5066.12	5069.45	5072.35	5065.71
BIC	5136.18	5084.89	5119.51	5159.95	5209.63
Log Likelihood	-2559.83	-2530.06	-2526.73	-2522.18	-2509.8
Deviance	5119.67	5060.12	5053.45	5044.35	5019.71
Num. obs.  ***p < 0.001, **p < 0.01, *p < 0.05	3855	3855	3855	3855	3855

Table: Testing for Racial Profiling of African Americans

### Veil of Darkness: WH and AA only



#### Summary: Veil of Darkness Tests

- Tests are inconclusive. Depends on how you control for time of day and year
- How to interpret? Failure to reject a hypothesis doesn't mean we accept it
- Further controls and estimation strategies