Analysis of Police Vehicle Stops in Cincinnati: A Geographic Perspective

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This study analyzes police vehicle stop data collected during the second half of 2001. In addition to addressing questions such as who is stopped and why vehicles are stopped, this article focuses on the geographic variations and racial variations of the stops in the fifty-two neighborhood areas of the City of Cincinnati. Racial disparities in vehicle stops are often linked to the controversial issue of racial profiling. A new measure, disproportionality, is developed to better capture such disparities. Many earlier studies used census population as the baseline in calculating disproportionality indices, based on an implicit assumption that people only drive in the neighborhood where they live. A reasonable baseline should reflect how many people drive in a neighborhood and how many miles are driven in a neighborhood. This study replaces census population by vehicle miles as the baseline. An innovative approach is developed to estimate vehicle miles in each neighborhood. The research concludes that small disparities exist between Black and White drivers in Cincinnati while the magnitude varies significantly by neighborhood areas, and that the spatial pattern of stops appears to be associated with those of driving patterns, crime, drug calls, overall demand for police services, and traffic accidents. Specifically, the correlations between stopping rates for African-Americans and accident rates and minor crimes are particularly high.

Key Words: *Traffic stops, police vehicle stops, racial profiling, policing, Cincinnati, GIS*

BACKGROUND

On March 28, 2001, the Cincinnati City Council passed an ordinance requiring the police to collect information on the race of people in vehicles stopped by police officers and required that the data from these records be analyzed by experts outside of the police department. This ordinance was the culmination of over a year's worth

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of public discussion regarding allegations that members of the police department unfairly targeted African-Americans—an alleged practice that many have called "racial profiling" (Engel et al., 2002).

The police department began collecting the required data on May 7, 2001 and established a competitive bidding process for the data analysis. The city issued a request for proposals to analyze the data on May 29th. The contract to analyze the police vehicle stops data was awarded to a team, made up of the authors of this article, from the University of Cincinnati on October 8, 2001. By January 27, 2003, all data covering stops from July 1, 2001 through December 31, 2001 had been entered into computer files and turned over to us. This time window was selected because we were concerned that data collected before July 1, 2001 would be unrepresentative of police stops, as officers had not become used to the new form and because of the events in April through June of that year.

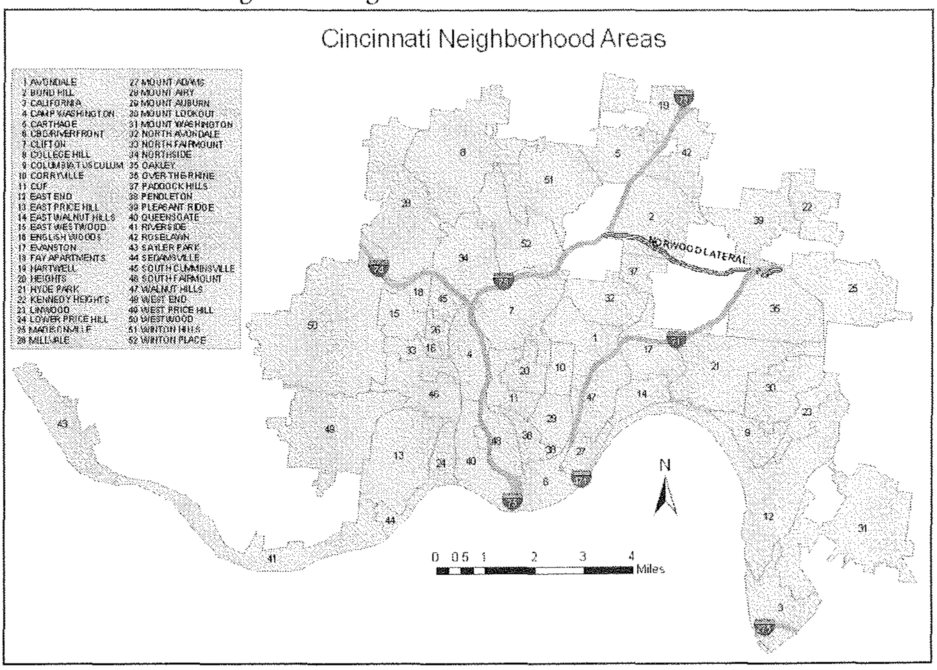
This is a controversial topic and the City Council wisely sought outside assistance to examine these data. It is important therefore to disclose the nature of police involvement in the production of this report. Throughout our work on this study, we met with members of the police department. The first meetings were to learn how the data were being recorded, and later meetings were held to assist the police department in developing a database that could be analyzed. Once the data had been entered into the database, the project team met monthly with members of the police department to describe our progress in correcting errors created when data from paper records were entered into the database. The research team also used these meetings to obtain additional information needed to analyze the vehicle stops data and to report on interim findings. At no time during any of these meetings did any member of the police department or city employee try to influence the way we conducted our analysis or how we interpreted the findings. In fact, members of the police department repeatedly and explicitly explained that they did not want to have any role in guiding the analysis or interpreting the findings.

In the spring of 2003 and in early September 2003, the project team briefed representatives of the collaborative parties. And on two occasions, the team briefed the City Manager, Valerie Lemmie. On one occasion, Councilman DeWine sat in on a briefing. Like members of the police department, these individuals made no effort to influence how we conducted our work. The result is that this report contains only our views, based on our interpretation of how the analysis of these data should be conducted and the meaning of the analysis results. The final report of this study was released on November 15, 2003. This article presents part of the overall findings.

WHAT WAS ANALYZED?

The data we analyzed for this report came from contact cards completed by police officers after they stopped vehicles. The terms of the city ordinance and the contract with the University of Cincinnati specify vehicle stops. Although officers also filled out these cards when making pedestrian stops, we did not analyze pedestrian stops because of the terms of the contract. Police data entry personnel manually entered completed cards into computer files. The police department then provided us with the computer files and copies of the original cards. The data were divided into three linked databases. One described the stops. Another described the occupants. And the third described the outcomes. The areal unit used for data collection and presentation is the neighborhood areas of Cincinnati (Figure 1).

Figure 1: Neighborhood Areas of Cincinnati.



All but 75 computer cases were checked against paper records for accuracy (about one percent). The team accepted what officers wrote on the forms, unless there was objective information available to indicate an error. Most information could not be independently verified. Errors on original records do not appear to be systematic but rather the normal result of everyday work.

We were able to identify discrepancies between the officers' cards and the computer records. There are two ways to assess the error rate. The first is the number of card entries with errors. As each card has multiple fields (check boxes and open boxes for entering information), we also examined the error rate for fields. The variation in error rates by database is shown in Table 1.

Table 1: Error rate (%) for data entry.

Database	Card Entries	Fields
Stops	38	3
Occupants	27	6
Outcomes	51	2

We checked almost all data fields and made corrections. The exceptions include descriptions of citizens stopped (e.g., height, weight, and hair color). When duplicate records were found in the computer records, we eliminated this redundancy. Record checking and error correction proceeded from July 2002 through May 7, 2003.

We reported to the Cincinnati Police the data entry problems throughout the process and the police made efforts to improve their systems accordingly. As noted above, the analysis examined stop data from July 1, 2001 through December 31, 2001. During this period, about 7,900 stops were made. Approximately 7,200 of these were vehicle stops. According to the contact cards, these stops involved around 10,800 people. Though officers usually completed all relevant fields on the cards, sometimes data were missing.

WHO IS STOPPED?

Officers completing the field contact card enter information on the race, gender, and age of the driver and occupants. We focus on the descriptions of the driver for three reasons. First, all vehicles have a driver. Second, as we show later, the major reason for stopping vehicles has to do with actions of the driver (i.e., moving violations). Third, mixed race vehicles were rarely stopped.

As can be seen in Table 2, stops are almost equally split between African-Americans and White. Because of the relatively few number of non-White and non-African-American drivers, in the analysis that follows we combine them into the category "other", which comprises 2.4 percent of the total. We report on the analysis for drivers of these other races, but we do not discuss these results as the small numbers and heterogeneous population make it difficult to draw any conclusions about police interactions with them.

Overall, the differences between the African-American drivers stopped and the White drivers stopped are slight. Drivers are predominately male, regardless of race (Table 3). With regard to age (Table 4), African-American drivers are slightly younger.

Police stops of vehicles show distinct temporal patterns reflecting the daily flow of traffic to and from work and evening entertainment. Figure 2 shows this rhythm for African-American and White drivers. Each radial line represents an hour block starting with midnight at the top, moving clockwise to noon at the bottom, and then back to midnight. The concentric rings are set at 2.5 percent intervals. The outer ring is at 10 percent. The lines trace the percent of drivers of each race stopped in each one-hour interval. Though the stops of African-Americans and Whites follow the same daily rhythms, there are some differences. Namely, stopping of White drivers is more common from 6 am to 5pm and stopping of African-Americans is more common from 5pm to 4am.

Table 2: Race of drivers stopped.

Race	Percent	Number
White	49.0	3491
Black	48.6	3460
Hispanic	0.7	48
Asian	0.6	44
Native American	0.0	3
Other	1.1	75
Total	100.0	7121

157 cases had no race information. This is about 2% of the 7278 vehicle stop cards

Figure 2: Stops by Hour.

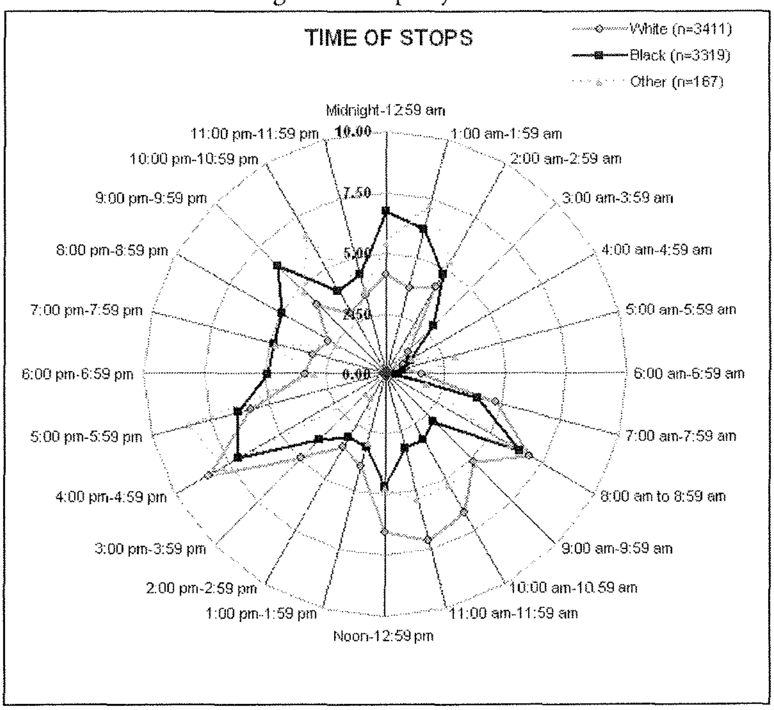


Table 3: Race and gender of drivers (%).

	White	Black	Other	All
Male	68.1	73.3	81.2	70.9
	(2376)	(2535)	(138)	(5049)
Female	31.9	26.7	18.2	29.1
	(1115)	(923)	(31)	(2069)
Unknown	0.0	0.1	0.6	0.0*
	(0)	(2)	(1)	(3)
Total	100.0	100.0	100.0	100.0
	(3491)	(3460)	(170)	(7121)

* Less than five one hundredths of a percent

Table 4: Race and age of drivers (%).

	White	Black	Other	All
Under 18	2.5	3.0	2.9	2.8
	(87)	(104)	(5)	(196)
18-25	33.1	39.3	38.2	36.2
	(1156)	(1359)	(65)	(2580)
26-35	26.5	26.4	32.4	26.6
	(924)	(912)	(55)	(1891)
36-45	19.9	18.8	15.3	19.3
	(696)	(652)	(26)	(1374)
Over 45	17.8	12.3	9.4	14.9
	(620)	(427)	(16)	(1063)
Unknown	0.2	0.2	1.8	0.2
	(8)	(6)	(3)	(17)
Total	100.0	100.0	100.0	100.0
	(3491)	(3460)	(170)	(7121)

WHY WERE VEHICLES STOPPED?

The field contact card lists seven reasons for a vehicle stop:

1. Moving violations include driving over the speed limit, making illegal turns, and other violations of traffic laws;
2. Equipment violations include non-functioning taillights, missing license tags, and similar problems;
3. Criminal offense includes the situations in which the occupants of the vehicle are suspected of a criminal act;
4. Suspect and vehicle description include situations in which the vehicle or the occupants appear to fit the description of people involved in some violation;

5. Stolen automobile involve situations where the officer making the stop believes the vehicle to be stolen;
6. Other reasons are not specified; and
7. Finally, officers may have failed to record a reason, so these are listed as "none".

Table 5 shows the frequency with which these reasons were recorded by officers (from most to least), and how the reasons vary by race. Moving violations account for over 70 percent of the reasons for stops. Stolen autos were the least frequent reason for stops. Within this pattern of similarity between Whites and African-Americans, there are also differences. Whites that are stopped are more likely to be stopped for moving violations than African-Americans. And, Whites were more likely than African-Americans to have "none" recorded on the contact card. African-Americans were more likely than Whites to be stopped for the other four reasons listed.

Table 5: Reasons for vehicle stops by race (%).

	White	Black	Other	All
Moving Violation	81.35	61.85	81.76	71.89
	(2840)	(2140)	(139)	(5119)
Equipment Violation	7.53	15.58	8.24	11.46
	(263)	(539)	(14)	(816)
Other Reason	3.15	7.69	1.18	5.31
	(110)	(266)	(2)	(378)
Criminal Offense	3.87	5.32	2.35	4.54
	(135)	(184)	(4)	(323)
Suspect/Vehicle Description	1.80	5.00	2.35	3.37
	(63)	(173)	(4)	(240)
None	2.23	1.73	4.12	2.04
	(78)	(60)	(7)	(145)
Stolen Auto	0.06	2.83	0.00	1.40
	(2)	(98)	(0)	(100)
Total	100.00	100.00	100.00	100.00
	(3491)	(3460)	(170)	(7121)

These six reasons for stops were combined into two categories: crime and non-crime. Crime includes criminal offense, suspect/vehicle description, and stolen auto. Non-crime contains all stops made for the other reasons: moving and equipment violations, other, and no reason given. Non-crime reasons for stops are the rule for both African-Americans and Whites. The most common non-crime reason for stops for African-Americans and Whites are moving violations. Whites are less likely than African-Americans to be stopped for an equipment violation. While African-Americans are over twice as likely to be stopped for crime-related reasons than Whites, Whites are far more likely to be stopped for a criminal offense than

African-Americans if they are stopped for a crime reason. Individuals in both groups are about equally likely to be stopped for a vehicle-suspect description or auto theft, if they are stopped for crime reasons.

HOW MUCH DISPROPORTIONALITY IN STOPS IS THERE?

In absolute numbers, Whites are stopped about as often as African-Americans (see Table 6). However, there are more Whites living in the city than African-Americans. According to the 2000 census, Whites comprise 56 percent of the city driving population, and African-Americans comprise 40 percent. We defined driving population as people ages 15 and older in year 2000. The geographical distribution of driving population for African-Americans and Whites is displayed in Figure 3. If the populations are unequal, but the two populations are similar in all other respects, then we would expect the proportion of Whites stopped compared to their numbers in the population to be similar to the proportion of African-Americans stopped compared to their numbers in the population. Using the 2000 census figures for people ages 15 and older, we see that the proportion of Whites stopped is not equal to the proportion of African-Americans stopped (Table 6).

For the average White motorist stopped within the 6 months studied, there is less than a 3 percent chance of being stopped. For the average African-American driver in this same time period, there is less than a 4 percent chance of being stopped. There is, in short, some basic disproportionality in police stops.

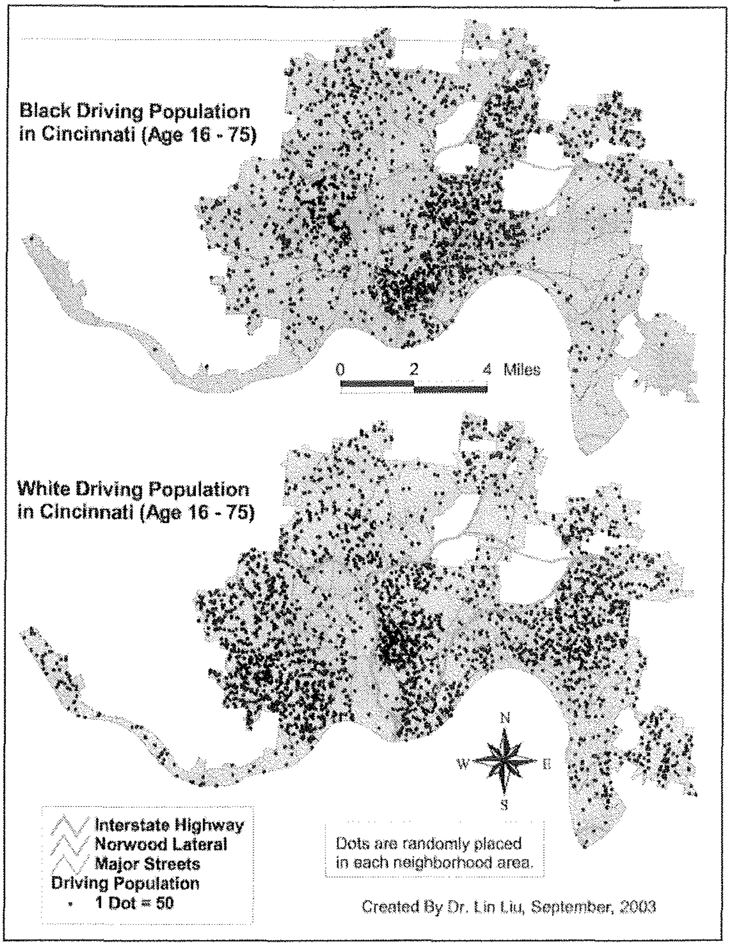
There are several things wrong with this analysis, at this stage. Some of these we can adjust for to make better estimates of disproportionality, and others we cannot adjust for, so we must live with the uncertainty.

These census figures do not consider that African-Americans may have been significantly undercounted in the 2000 Census. If there are significantly more driving age African-Americans living in Cincinnati than counted by the census, then the level of African-American disproportionality is less than shown in Table 7. Undercounting of Whites would produce the opposite effect.

Table 6: Proportion of races stopped.

	Stops (Contact Cards)	Percent of total stops	Driving Population (2000 Census)	Percent of total population	Percent of population stopped
Whites	3491	49.02	131,271	55.92	2.66
Blacks	3460	48.59	93,978	40.04	3.68
Other	170	2.39	9,486	4.04	1.79
All	7121	100.00	234,735	100.00	3.03

Figure 3: Driving Population by Race in Cincinnati Neighborhoods.



Second, there is considerable commuter traffic into and out of Cincinnati. The police sometimes stop these individuals. So, the "at risk" population is not just the resident population. To the extent that Whites commute into and through Cincinnati in greater numbers than do African-Americans, then not accounting for this will underestimate African-American disproportionality. For this reason, we put considerable effort into estimating the commuter population and its racial composition. We will describe this later, but for now we must note that these estimates are not perfect, so measures of disproportionality based on them will not be precise. Though we have attempted to adjust for the daily rhythm of commuting, we could not adjust for other events that bring people into the city on a more sporadic basis. We do not know if such people are more likely to be White or African-American.

Table 7: Disproportionality indices for Cincinnati neighborhoods (ranked by vehicle mile index).

Neighborhood Areas	Based on vehicle miles	Based on driving population	Neighborhood Areas	Based on vehicle miles	Based on driving population
CUF	3.24	3.29	Bond Hill	1.25	0.98
Clifton	2.89	3.31	Madisonville	1.24	1.03
Mount Lookout	2.86	11.63	Over-The-Rhine	1.23	1.07
Clifton Heights	2.63	2.85	Walnut Hills	1.22	0.84
East Price Hill	2.32	2.79	Avondale	1.22	0.88
Winton Place	2.30	1.68	Roselawn	1.19	0.95
Oakley	2.16	3.02	Mount Washington	1.13	1.29
Corryville	2.04	1.61	Fay Apartments	1.12	0.91
Camp Washington	2.00	1.49	English Woods	1.11	1.02
Pleasant Ridge	1.88	1.70	Hartwell	1.11	1.10
Westwood	1.83	1.74	Millvale	1.10	0.90
Carthage	1.79	1.70	Riverside	1.10	1.13
Paddock Hills	1.75	1.48	Mount Adams	1.09	1.20
Northside	1.73	1.60	North Fairmount	1.07	1.05
California	1.71	17.80	Kennedy Heights	1.07	0.97
Lower Price Hill	1.69	3.06	West End	1.00	0.71
Mount Auburn	1.58	1.16	Pendleton	0.96	0.81
South Fairmount	1.55	1.40	Columbia Tusculum	0.93	1.21
Winton Hills	1.44	0.98	Queensgate	0.84	0.37
College Hill	1.37	1.28	Hyde Park	0.76	1.42
East Westwood	1.37	1.24	Evanston	0.67	0.52
North Avondale	1.35	1.13	Linwood	0.58	3.58
East Walnut Hills	1.34	1.06	South Cumminsville	0.48	0.36
West Price Hill	1.33	1.43	East End	0.39	0.58
CBD/Riverfront	1.28	0.56	Sayler Park	0.00	0.00
Mount Airy	1.27	1.09	Sedamsville	0.00	0.00

But perhaps the most troublesome issue is how to adjust for differences in prevalence in deviant behavior that the police may observe. This is a controversial issue in itself, though it should not be. We know from innumerable studies that crime is concentrated in poorer neighborhoods and in the United States such neighborhoods tend to have high concentrations of African-Americans (National Research Council, 2003; Sampson and Lauritsen, 1997). Cincinnati is like many other cities in this regard. Such neighborhoods also tend to place greater demand on police services, apart from crime (Sherman and Eck, 2002). The result is twofold. First, more police are deployed to these neighborhoods because there is more police work in such neighborhoods. This increases the exposure of drivers to police officers. So, an individual engaged in a traffic infraction who might not be noticed in a low crime neighborhood with few police is more likely to be noticed in a high crime neighborhood with many police. Offsetting this, however, is the fact that the police are busier, despite their greater numbers, so they may overlook some infractions. The second effect is that with more crimes police will make more stops of suspicious individuals. Some of these stops will result from citizens reporting and some will result from actions initiated by the police themselves.

To address these issues we use maps to show where stops take place. We also adjusted the base population by the miles driven by African-Americans and Whites. We then measured disproportionality in each neighborhood. Finally, we compared maps of stops and disproportionality to maps of crime, drug calls, calls for police services, and traffic accidents. We describe these procedures and results next.

Locating vehicle stops

Using mapping software, we attempted to place each vehicle stop on a computerized street network map provided by the Cincinnati Area Geographic Information Systems (CAGIS). We matched the address of each vehicle stop to a corresponding street on the map. The exact location of the stop was determined by a linear interpolation process that fitted the address number of the stop to its position in the address range of the street. Even address numbers are placed to one side of the street and odd numbers to the other side. This process is called geo-coding.

About 5 percent of the stops could not be geo-coded due to the following reasons:

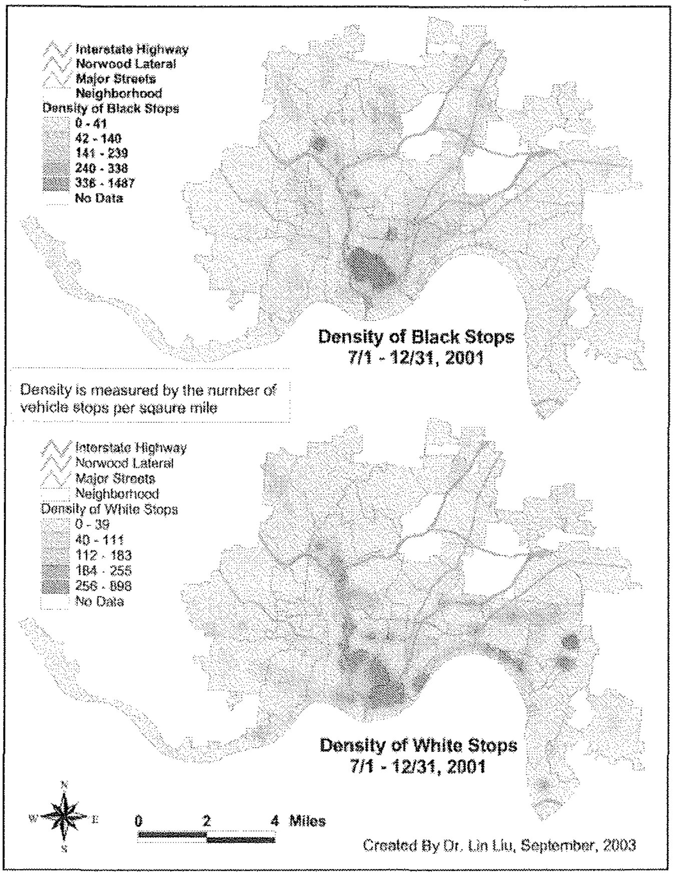
- The street listed on the contact cards did not correspond to a street on the computer map;
- The address number listed on the contact card were outside of the address range of the street; and
- The address on contact cards is outside of the City of Cincinnati.

A 95 percent geo-coding rate is well within acceptable limits for data of this type.

We then matched the geo-coded stops to the occupant database to obtain occupant information for each stop. A small number of stops did not have occupant information. The total number of vehicle stops in this part of the analysis is 6,854.

Figure 4 shows the geographic distribution of vehicle stops by race. Instead of using a dot map where multiple stops at the same location are represented as a single dot, we mapped the density of vehicle stops. Density is measured as the number of stops per square mile. Although there is substantial geographic overlap between African-American and White stops (particularly in and around the central business district, and the I-75 corridor from downtown to Northside), there are important differences. In particular, White stops are somewhat more heavily concentrated along major commuter routes than are African-American stops. These differences are reflected in day and night stops for both races.

Figure 4: Spatial Distribution of Vehicle Stops by Race.



Calculating disproportionality index

The disproportionality of Black stops is typically measured as a ratio of the number of Blacks stopped (Bs) to total number of stops (Ts) divided by Blacks base driving population (Bb) divided by the total base driving population (Tb):

Black disproportionality index = (Bs/Ts) / (Bb/Tb).

When the disproportionality index equals 1 there is no disproportionality. A disproportionality index larger than 1 suggests Blacks are stopped more frequently.

The count of stops in the numerator of the index comes from the geo-coded vehicle stops aggregated to Cincinnati neighborhood areas. The denominator, however, is very difficult to estimate. As noted above, raw census figures do not provide a valid way of measuring disproportionality, given commuting patterns. Our analysis indicates that the white/black driver ratio during commuting hours is about twice the ratio of the white/black residential driving population. Therefore, using population as the baseline will lead to incorrect conclusions. This is consistent with the findings of earlier studies, which argue that the census population is not a reasonable estimate of denominators in calculating the disproportionality index (Engel et al., 2002).

We developed a new approach for estimating the baseline data. Instead of estimating the number of drivers by race, we estimate vehicle miles by race. This approach not only takes into account people who live outside the city and commute in or through Cincinnati, it also takes into account their exposure to police. A person driving 40 miles per day has more exposure to police than a person driving 5 miles per day. The vehicle miles in a region is the sum of miles driven by all drivers.

We used the average daily traffic counts from the Traffic Engineering Department of the City of Cincinnati to estimate the total vehicle miles in each neighborhood. To obtain vehicle miles by race, we made the following assumptions:

- vehicle miles during rush hours are influenced by commuters;
- vehicle miles during daytime (excluding rush hours) are influenced by the daytime driving population;
- vehicle miles during nighttime are influenced by nighttime driving population.

Rush hour vehicle miles by race

Analysis of a sample detailed daily traffic counts from the City Traffic Engineering Department suggested that, on average, traffic counts during rush hours contribute about 23 percent of the total daily traffic count. Therefore, it is reasonable to assume that 23 percent of the daily vehicle miles come from rush hours.

To obtain the race of drivers during rush hours we decided to send students to observe the rush hour traffic.[1] All student observers attended a one-hour in-class training of the procedure and outdoor experimental observations. All observers used a standard form to document the results of observation. The race of drivers is coded as "W" for Whites, "B" for Blacks, "O" for others, and "U" for undecided. The "U" counts were later distributed to the other three categories based on their proportions. A team of two observers was sent to every site. Team members simultaneously and independently observed 15 minutes of traffic in each direction of a street segment. A total of 126 sites were observed during late spring and early summer of 2002 and early spring and late summer of 2003. There are possible small over counts of Whites and Blacks because Hispanics may have been counted as either. Except for one site, the results of the two observers were consistent. The data from these observations were applied to estimate the rush hour vehicle miles of African-Americans and Whites during rush hours.

The remaining 77 percent of vehicle miles were divided evenly to daytime and nighttime. An even division is consistent with the general trend suggested by detailed daily traffic counts from the City Traffic Engineering Department.

Daytime vehicle miles by race

In 1995 the U.S. Department of Transportation published a "trip table" documenting the number of people traveling from one traffic analysis zone (TAZ) to work in another TAZ (BTS, 1995). This table is based on the 1990 census. A table based on the 2000 census is not available. To estimate the trip table for 2000, we calibrated the 1990 trip table by using the daily traffic counts from the City Traffic Engineering Department and a recommended "bi-level traffic assignment optimization approach" (Chen, 1994). This calibrated trip table together with 2000 census data provided us the estimates of daytime driving population by race for each neighborhood area. This race data was applied to 38.5 percent of the daily vehicle miles.

Nighttime vehicle miles by race

The race of drivers at night is influenced by the nighttime driving population, which we estimated from the 2000 census data. These race data are applied to the remaining 38.5 percent of the daily vehicle miles.

Adding the three components—rush hour, day non-rush hour, and night—gives the total vehicle miles by race. The geographic distribution of the vehicle miles of African-Americans and Whites is displayed in Figure 5. With the vehicle miles, the disproportionality index for Black stops was calculated using the formula above but substituting the vehicle miles of black driver (Bv) for the African-American population of a neighborhood and the total vehicle miles (Tv) for the total population of a neighborhood. The resulting formula thus reads:

Black disproportionality index (based on vehicle miles) = (Bs/Ts) / (Bv/Tv)

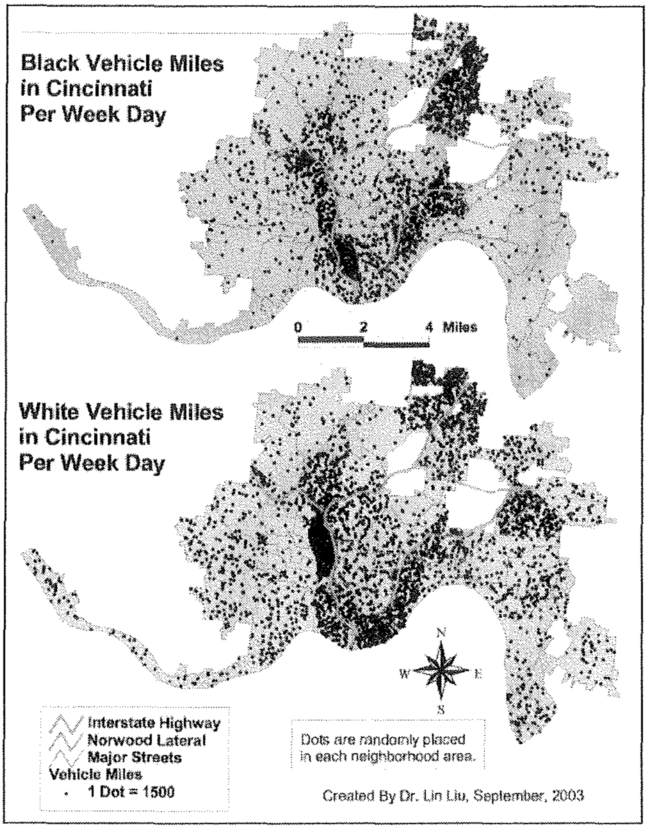
The disproportionality indices of Blacks by census driving population and by vehicle miles are shown in Table 7. The indices are also represented as choropleth maps (Figures 6 and 7).

Though we believe that the estimates of disproportionality based on vehicle miles are more accurate than estimates based simply on census data, the index numbers should be considered only approximations. For this reason, more attention should be paid to broad groupings of neighborhoods than individual neighborhood index numbers.

To allow for small variation on either side of exact proportionality, we attributed the highest 5 percent of the interval from 0 to 1 and the smallest 5 percent of the interval from 1 and higher to a neutral category. Neighborhoods with a disproportionality index within this neutral interval have roughly proportional stopping of Whites and African-Americans. These 9 neighborhoods are shown in Figure 7 and in Table 7 in gray.

Nine neighborhoods had index numbers below the neutral interval, indicating disproportionate stopping of White drivers. Sedamsville and Sayler Park have an index of zero because no African-American drivers were stopped in these two neighborhood areas from July 1 to December 31 of 2001.

Figure 5: Vehicle Miles by Race in Cincinnati Neighborhoods.

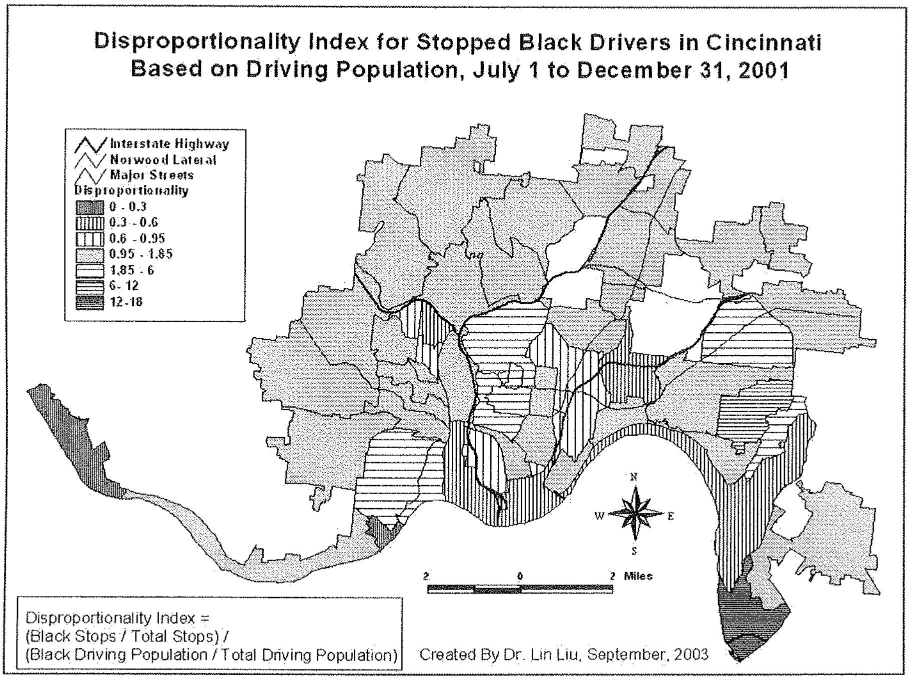


Thirty-four neighborhoods had index numbers above this neutral interval, indicating disproportionate stopping of African-American drivers. Of the 34 neighborhoods with notable African-American disproportionality, 25 had index numbers below two, indicating relatively low levels of disproportionality. The extreme high value of CUF may be an indication of an underlying problem, but it could be due to stops along several arterial routes along its periphery, or to errors in the estimation process.

Explaining stops

Table 8 shows the correlation of vehicle stops with other race neutral factors, including traffic accidents (Figure 8), calls for service (CFS) (Figure 9), drug-related calls (Figure 10), serious (part 1) crimes (Figure 11), and minor (part 2) crimes (Figure 12).

Figure 6: Disproportionality Index for Black Drivers Based on Driving Population in Cincinnati Neighborhoods.



These correlations show how the vehicle stop rates in neighborhoods vary with each of these other factors. If the correlation between stops and a factor is greater than zero, then neighborhoods with more stops have more of the factor, and vice versa. If the correlation is less than zero, then neighborhoods with more stops will have less of the factor. If the correlation is zero, then there is no relationship between stops and the factor in question.

Significance tests are used to rule out random fluctuations as a possible cause of a correlation. Significant correlations have little chance of being caused by randomness. In Table 8, significant correlations are marked with an asterisk (*). If a correlation is not significant, this means randomness may have been the cause, but we cannot be sure. Significance tests are particularly important with small numbers of cases. In this analysis neighborhoods are the cases, and there are only 52 of them. In Table 8, the numbers in the columns labeled "significance" give the probability that the adjacent correlation is due to random fluctuations. Probabilities of .05 and lower are deemed significant, by normal social science standards. So, for example, the correlation between White vehicle stops and Part I crimes (.312) is significant because there is only a .025 probability that a correlation of this size could have arisen by chance. However, the correlation between African-American stops and Part I crime (.176) is not significant because there is a .211 probability that a correlation of this size could have arisen by chance alone.

Figure 7: Disproportionality Index for Black Drivers Based on Vehicle Miles in Cincinnati Neighborhoods.

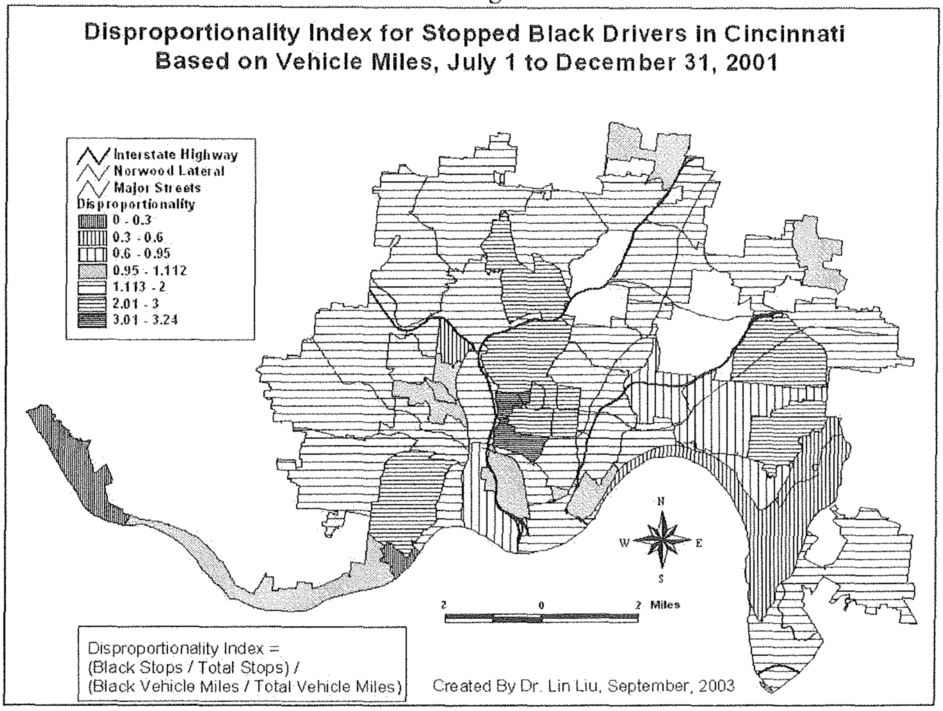


Table 8: Correlations of vehicle stops with other factors (n=52 neighborhoods).

	White stops/Vehicle mile		Black stops/Vehicle mile		All stops/Vehicle mile	
	Correlation	Sig.	Correlation	Sig.	Correlation	Sig.
Accidents/ Vehicle mile	.322(*)	.020	.698(*)	.000	.484(*)	.000
Calls for service/ population	.445(*)	.001	.250	.074	.403(*)	.003
Drug Calls/ population	.265	.057	.200	.155	.292(*)	.036
Part I Crime/ population	.312(*)	.025	.176	.211	.277(*)	.047
Part II Crime/ population	.445(*)	.001	.309(*)	.026	.483(*)	.000

* Correlation is significant at the 0.05 level (2-tailed).

Figure 8: Spatial Distribution of Traffic Accidents.

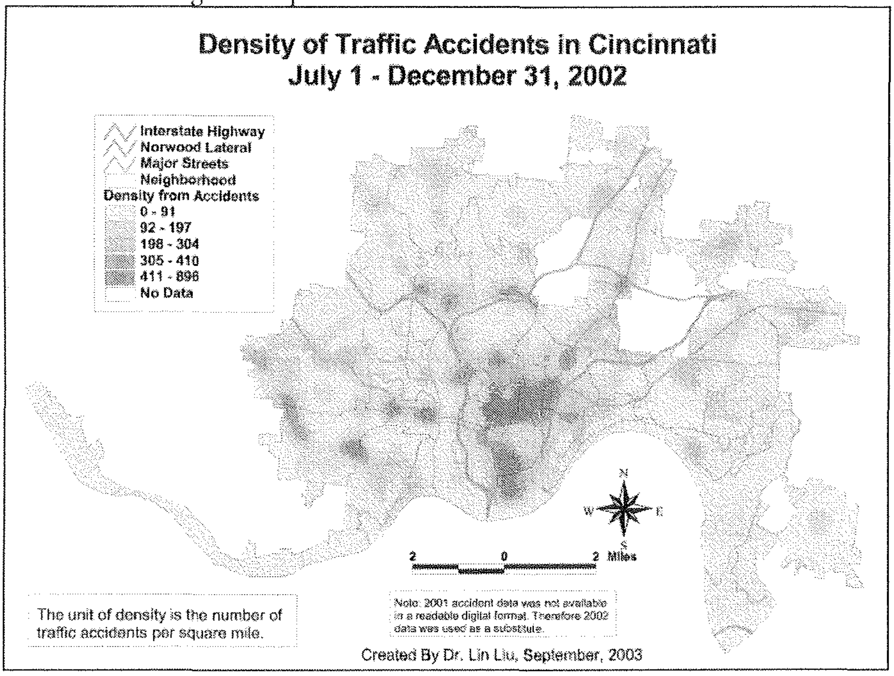


Figure 9: Spatial Distribution of Calls for Service.

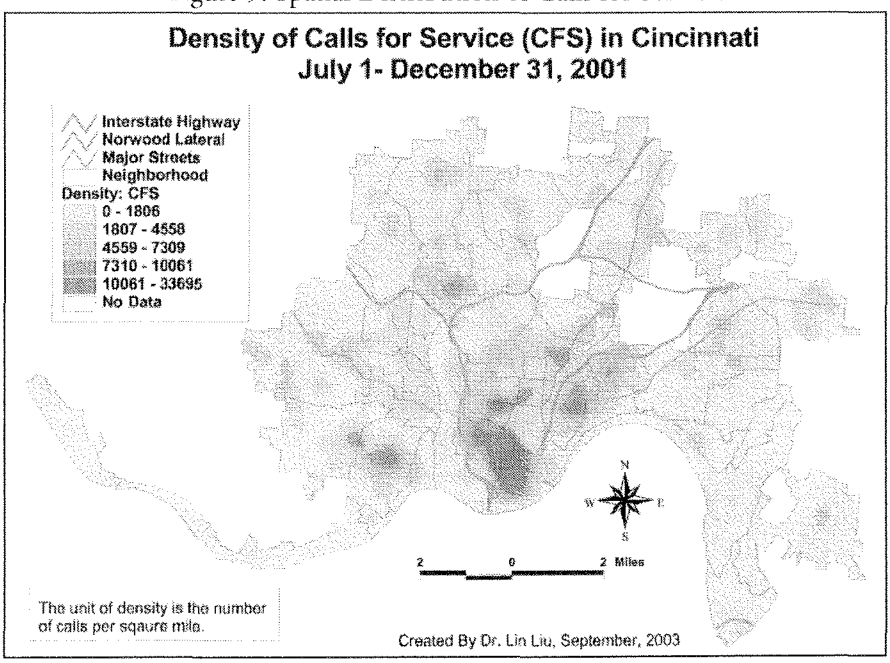


Figure 10: Spatial Distribution of Drug Related Calls for Services.

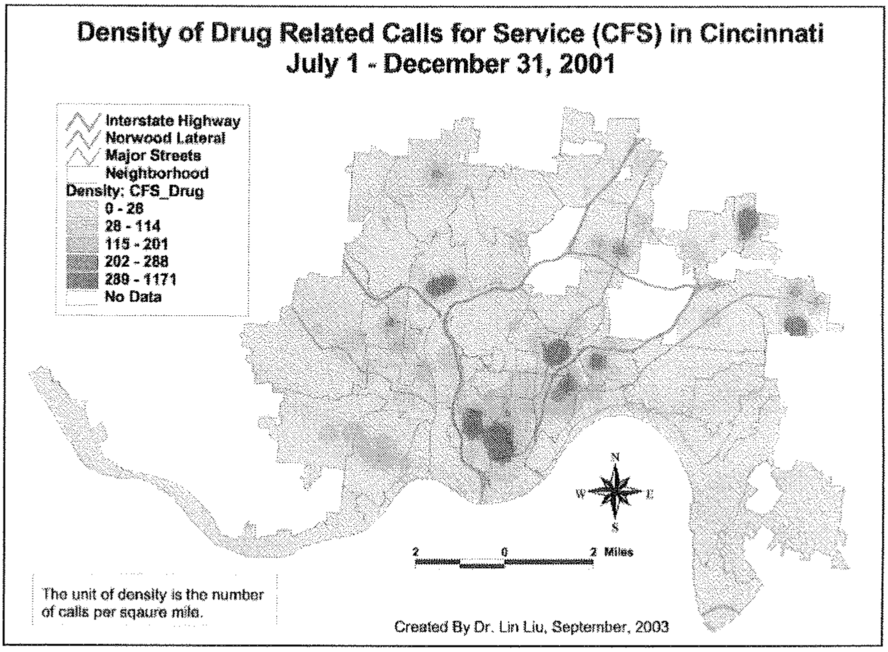


Figure 11: Spatial Distribution of Serious Crime.

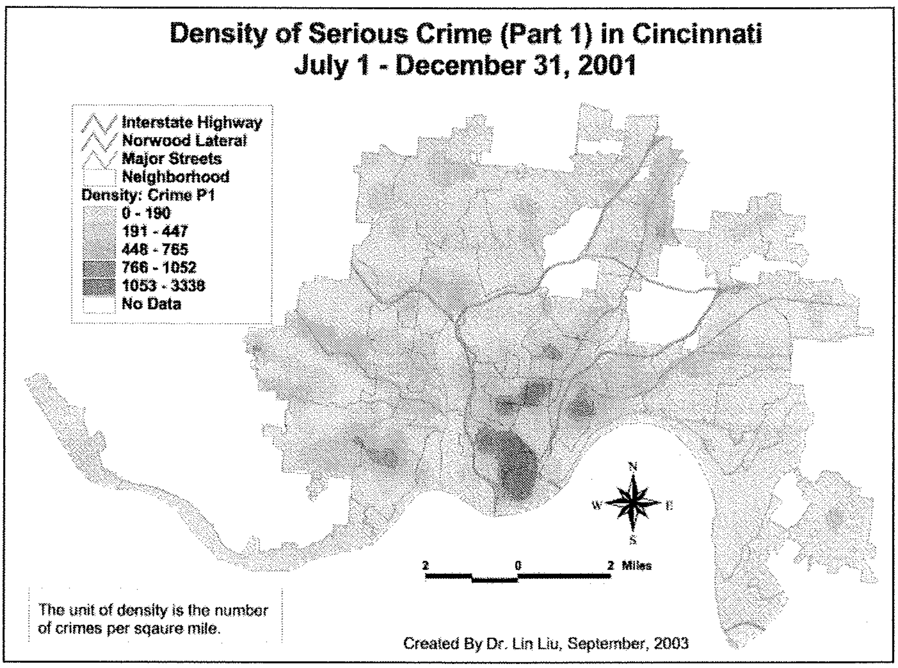
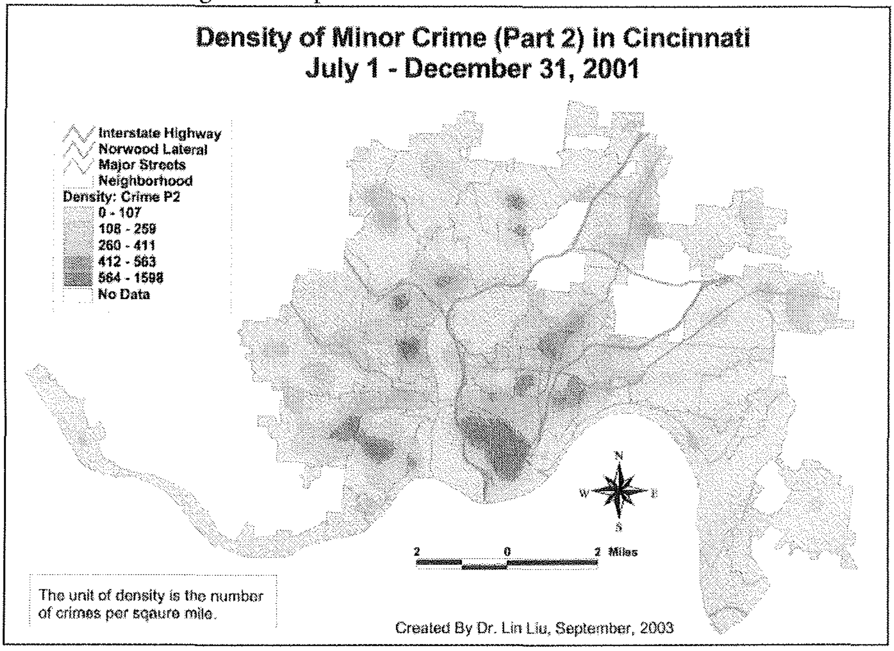


Figure 12: Spatial Distribution of Minor Crime.



Each of the six factors measures a different type of police workload in a neighborhood. We would expect that as each increases, vehicle stops would increase (positive correlations), for two reasons. First, the more of these events the more police are in a neighborhood to deal with these events. This exposes neighborhood drivers to more police who might see misbehavior. Additionally, the police use these types of measures to determine how many officers to deploy to parts of the city. Second, as these events increase, police may become more proactive and use stops to prevent future occurrences. The importance of these two explanations will vary by the type of workload. So for example, calls for service probably operates more by just bringing in more police to handle the calls, but may not have much effect on proactive police work. Drug calls and serious crime may influence traffic stops by both mechanisms.

We normalized stops by vehicle miles. For the workload factors, we normalized accidents by vehicle miles, the other factors we normalized by driving population. These normalizations remove the influence of varying population and/or vehicle miles in different neighborhoods. Total stops are significantly correlated to accidents, CFS, drug related calls, serious crime, and minor crime. Stops of African-American drivers are significantly correlated to accidents, and minor crime. Stops of White drivers are significantly correlated to accidents, CFS, serious crime, and minor crime. We do not have an explanation for the reasons for these differences in correlations. We can say that to a large degree, vehicle stops are highly related to police workload factors in neighborhoods, in addition to vehicle miles driven. The implication of this finding is that at least some of the disproportionality identified above is due to demands on the police as expressed by higher rates of accidents, larger workloads, crime rates and drug calls.

DISCUSSION AND CONCLUSION

This study found that there are small but important differences in who is stopped between African-Americans and Whites. The group of African-Americans stopped by the police from July 1 through December 31, 2001 tended to contain more males and was somewhat younger than the group of Whites stopped during this time. Stops of White drivers were more likely to occur during the day than were stops of African-American drivers.

African-Americans and Whites were most often stopped for moving violations. However, more African-American drivers were stopped for crime- related reasons than Whites. This may be due to racial disparities in income. Nevertheless, the impact of equipment violation stops falls more on African-Americans than Whites. An unequal impact such as this requires a demonstrated public benefit to justify it. From these results, we conclude that African-Americans and Whites may not have been engaged in identical behaviors prior to being stopped. An important question resulting from this part of the analysis is "why are African-American drivers stopped more for equipment violations than Whites? "

African-American drivers are a bit younger than White drivers. Within the age range we are concerned with in this study (15 years old and higher) young people are known to be more likely to be involved in deviant behavior than older people. This is true regardless of race and is very well documented in criminological research.

A slightly higher proportion of the African-Americans who are stopped are males than is the case with Whites who are stopped. This corresponds to another known criminological fact: males tend to be more involved in deviancy than females.

These findings are consistent with the finding that African-Americans are more likely to be stopped for crime related reasons than Whites. Though these differences are not immense, they are consistent. Collectively they support the hypothesis that some portion of the disproportionality observed is due to disproportionate involvement in crime and disorder. That is, the disproportionate stopping of African-Americans may be due to officers reacting to behaviors they observe rather than officers seeking to stop African-American drivers in preference to White drivers.

To determine if African-Americans are over-represented among those stopped, we used the most recent census information and models of driving patterns in the Cincinnati region. Our index of disproportionality based vehicle miles varies over Cincinnati neighborhoods. However the magnitude of variation is smaller than that of driving population based disproportionality. It is reasonable to conclude that our disproportionality index is more accurate than the indices used in earlier studies (Engel, et al, 2002), and that our approach of estimating vehicle miles in neighborhood areas can be applied to other cities.

The spatial pattern of stops appears to be associated with the spatial patterns of driving patterns, crime, drug calls, overall demand for police services, and traffic accidents. The correlations between stopping rates for African-Americans and accident rates and minor crimes are particularly high.

To what extent are these results generalizable? We have no confidence that these results are generalizable to time periods prior to July 1, 2001. The very existence of the forms to record data on the race of individuals stopped by the police may have changed police behavior. Further, events in the year leading up to July, 2001 are likely to have had an impact on officers' perception of their work, how they did their job, and on how citizens react to officers.

We are somewhat more confident that these results are generalizable forward in time. But again, we must exercise considerable caution. During the time period we examined, officers may have been stopping fewer vehicles and may have been particularly reticent about stopping vehicles with African-American drivers. If this was the case, our results might understate current levels of African-American disproportionality. On the other hand, the events of 2001 and the implementation of the collaborative agreement may have altered the way police interact with citizens in ways that reduce African-American disproportionality. Until analyses similar to these have been conducted, we will not be able to answer this question.

A major limitation in these data is the lack of an historical perspective. Tracking how officers make stops over time will provide information on trends in disproportionality and will allow policy makers to examine the impacts of police practices on disproportionality. As important, consistent reporting of disproportionality, along with crime data, will help assure the public that both are being addressed. As important as documenting how police conduct stops of citizens, we must emphasize that data from these stops only provide an incomplete picture of how and why disproportionality arises. Other information needs to be sought to develop appropriate policies to limit disproportionality.

NOTE

1. We first explored using digital images/videos to capture rush hour traffic and analyze them on a computer. However, due to early sunlight, the quality of the digital images/videos was less than desirable and the results were not satisfactory.

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