An Empirical Investigation of the Possible Presence and Extent of Arbitrary Profiling in the Charlotte-Mecklenburg Police Department

Final Report to Charlotte-Mecklenburg Police Department

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January 16, 2004

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Executive Summary

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Of Final Report:

An Empirical Investigation of the Possible Presence and Extent of Arbitrary Profiling in the Charlotte-Mecklenburg Police Department

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This report examines whether and to what extent the Charlotte-Mecklenburg Police Department (CMPD) arbitrarily profiles citizens in their jurisdiction. For purposes of this report, citizens who have been stopped or otherwise detained based on demographic characteristics, such as race, rather than on the objective behaviors of the citizens are defined as having been subject to arbitrary profiling. The information used in the analysis include the vehicular and pedestrian stop data provided by the CMPD, accident data obtained from the North Carolina Division of Motor Vehicles, and demographic data compiled from the U.S. Census Bureau. In addition, citizens' calls for service (911 calls) are utilized to help determine whether the stops and searches in various areas of the city are consistent with citizen demands for policing in those same areas. Traffic accident and census data are used to create estimates of the racial composition likely to be found in particular areas of Charlotte-Mecklenburg and thus provide baselines for comparisons with the CMPD stop and search data. **In general it is found that stops and searches are largely accounted for by demand for police services and success in finding contraband, and not the demographic characteristics of the citizens. Still, the analyses do identify particular geographic areas where the number of African Americans stopped and/or searched surpass what we would expect given our prediction models. In other areas, however, there are fewer African Americans stopped and/or searched than the statistical evidence indicates would be expected. Several possible reasons for these disparities are addressed and discussed.**

Our task as researchers is to provide an empirical assessment, within the limits of the data available to us, of the degree of racial and other disparities in the stops and searches of pedestrians and of vehicles. Whether a specific level of disparity is excessive ultimately depends on what is deemed appropriate levels of enforcement by the CMPD the citizen advisory board of this project, and the Charlotte-Mecklenburg community. Our report provides descriptions and estimates of disparity across groups. Because age and gender are well known correlates of violation behaviors -- with men and the young more active --- we expect, and find, more stops and searches of these demographic groups. **We focus on disparity in the stops and searches of African Americans, as this group is most discussed as the target of racial or arbitrary profiling.**

There are **four primary outcomes** that we evaluate**: 1) pedestrian stops, 2) vehicular stops, 3) consent searches at pedestrian stops, and 4) consent searches at vehicular stops.** In all four instances we find that there are **some districts with more African Americans stopped or searched than we would expect**, given the demographic makeup of the area and the demand for police presence as reflected in the area's calls for service. At the same time **there are some districts with fewer African Americans stopped or searched than we would expect.** The information available to us and the resulting prediction models do not allow one to make a definitive claim that those areas with greater numbers of African Americans stopped or searched indicate areas where racially biased policing is taking place. Similarly, we do not know why, with certainty, some areas show lower numbers of stops and searches of African Americans than our model of such processes leads us to expect. We do discuss some possible explanations for these results, but decision makers must evaluate all of the evidence, including information not available to us as researchers, to determine the extent to which racial bias may be a contributing factor and what remedial steps may or may not be necessary.

Summary of Findings for Pedestrian Stops

Approximately seventy-four percent of the 5,649 citizens stopped by the CMPD in Charlotte-Mecklenburg were African American. The first question we address is whether the number of pedestrians stops is a function of demand for service in geographic areas. We defined as geographic areas the census defined block groups (roughly 1,800 people per block group, with 373 in Charlotte). **We tested various factors as being predictive of the number of pedestrian stops and found that there were two important predictors (in regression equations) of the overall numbers of pedestrian stops and the number of pedestrian stops of African Americans. These factors were 1) demand for service for what we call "incivility" calls for service (citizen calls to police for prostitution, drugs, inebriated pedestrians and fights), and 2) success in searches. Racial composition of an area was found to have no independent effect on the number of stops when the other factors were controlled for statistically in the model.** (See Table ES1 for a summary of the important factors found to be predictive for each of the outcomes examined in the analysis.)

These results do not indicate that all sub-areas of the city are within a normal range of pedestrian stops of African Americans, however. **Figure ES1 below shows that some census block groups (each square on the figure represents one or more census block groups) have more African Americans stopped in that census block group than our model predicts, while others have less.** The predicted value for each census block area is the center diagonal line. These values are predicted using a regression equation. The middle red line in the figure is the regression line and represents the expected number of African Americans that should be stopped, given the known influence of the demand for service for incivility offenses and the success at finding contraband in the form of drugs and alcohol. The two lines running parallel with the

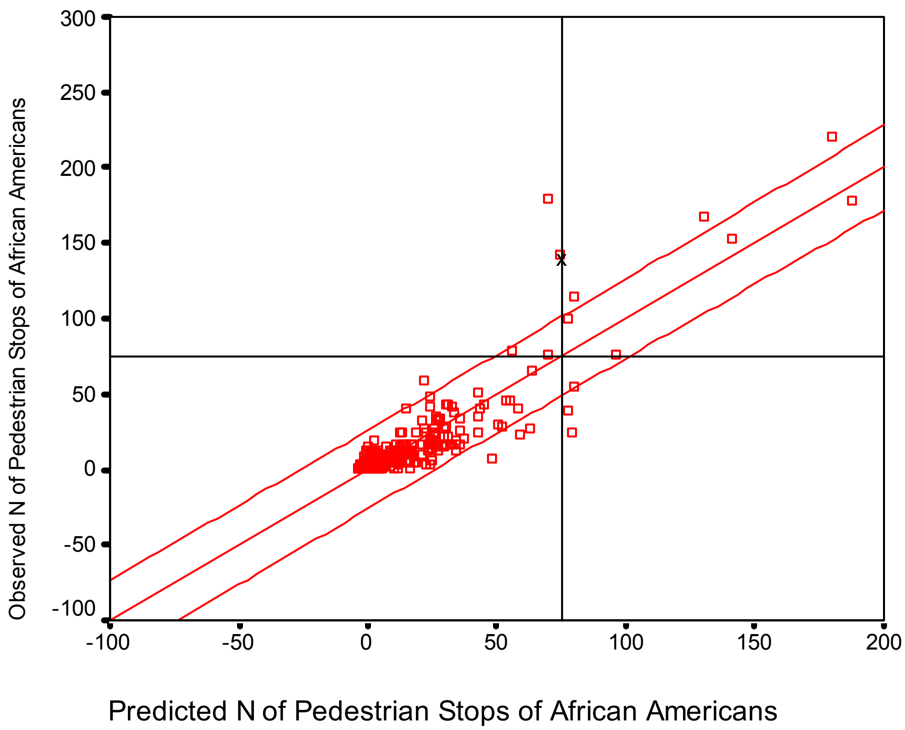
Table ES1 Summary of Key Findings

Outcome	**Important Predictive Factors**
N of Pedestrian Stops	N of Calls for Service for Incivility Offenses N of Successful Consent Searches in Pedestrian Context (Drugs or Alcohol Found)
N of Driver Stops (Vehicle Stops)	N of Drivers in Accidents N of Successful Consent Searches in Vehicular Context (Drugs or Alcohol Found)
N of African American Pedestrian Stops	N of Calls for Service for Incivility Offenses N of Successful Consent Searches in Pedestrian Context (Drugs or Alcohol Found)
N of African American Driver Stops (Vehicle Stops)	N of White Drivers Stopped N of African American Resident Population N of African Americans in Accidents N of Successful Consent Searches in Vehicular Context (Drugs or Alcohol Found)
N of African American Pedestrian Consent Searches	N of Calls for Service for Incivility Offenses Success Rate of African American Consent Searches in Pedestrian Context (Drugs or Alcohol Found)
N of African American Consent Searches in Vehicular Context	N of Calls for Service for Incivility Offenses N of Stops of African Americans in Vehicular Context

predicted regression line represent 95% confidence intervals of the predicted values. **We define "outliers" as the values that lie outside this confidence interval**. Census block groups below the lower diagonal line represent those with fewer African Americans stopped than the model would lead us to expect.

Also note that there are two perpendicular "reference lines" in the figure – each corresponds to the value of 75, arbitrarily chosen to show that when the regression line predicts that 75 African American pedestrians should be stopped, we have no census block group with exactly 75 African Americans stopped as pedestrians. However, we do

Figure ES1. Predicted Number of African Americans Stopped as Pedestrians by Observed Number of African Americans Stopped



have a positive outlier with approximately 140 African American pedestrians stopped. This outlier is marked with an “x”. It would be useful to be able to determine why this census block group, in particular, -- with 65 more African American pedestrians stopped than the 75 predicted by the model -- as well as the other four positive outliers, does not conform to our prediction. Unfortunately, we do not have data that allow us to more directly account for these outliers.

Factors not examined here may account for the “low” or “high” numbers of African American pedestrian stops. Census block group areas with relatively high numbers of African American pedestrians (“positive outliers”) could be the result of unique aspects of the neighborhoods in question, such as a history of drug problems or known drug traffickers not adequately measured by the 911 calls. Other omitted factors could include community and political groups who request additional policing in high need neighborhoods. Neighborhoods with greater levels of community policing may have higher numbers of African Americans stopped, relative to the demand and search success factors used in our model.

Figure ES1 and the geographic location of the outliers were presented to local police leaders. **Some possible factors to explain the positive outliers** were noted by the police leaders familiar with the areas in question. These factors include: 1) the presence of a **local college** (historically African American) – which may account for more African American pedestrians than in other areas, all else being equal; 2) the presence of a **public housing complex** with a history of drug-related problems; 3) an area may have been defined by the police as a **“hot spot”** and thus subject to an “aggressive” police presence (including bike patrols) to address the problems in that area; 4) the presence of

convenience stores (where alcohol is sold) and "winos" hang out – the latter are often the subject of pedestrian stops; 5) a **"red light" area** where street prostitution is a problem that occupies the attention of the police; 6) the presence of a **large "homeless" population** near the city shelter and soup kitchen (presumably there is a greater police presence and pedestrian searches are incidental to that presence; also some of the behaviors of the homeless are triggering the police stops); 7) the area is **a central downtown area** (where there are many pedestrians due to the concentration of people in relatively small areas); and 8) the area is near one in which there are many **"special events"** (e.g., stadium events).

Negative outliers – areas with "too few" African American pedestrian stopped (that is, the census block area found to be below the confidence interval of the prediction model) might be accounted for by the following factors (again according to local police leadership): 1) the area is subject to **a federal drug enforcement** effort so local police have less of a role; 2) the area is **largely Hispanic** (thus, there would be fewer African Americans stopped); 3) the area is where there has been "**Neighborhood Action Teams**" involved to reduce crime – this type of police presence is less oriented to stop and search interventions; 4) the area includes a **research park** (where presumably there is little activity at night, low crime, and (possibly) relatively few African Americans – driving down the total numbers of African Americans for the whole census block group); 5) area is "hard to get to" in that there is **no "thoroughfare" running through the area** (thus, police presence would be less than otherwise would be the case); and 6) some officers are **under-reporting their stops** (not filling out the stop forms). In the course of the discussion it was mentioned that a couple of the negative outliers did not seem to have any obvious explanations other than they were next to an area that was a positive outlier, suggesting **a "lightning rod" effect** where one neighborhood drew the police attention while the other did not (despite having a high volume of calls for service for incivility offenses.)

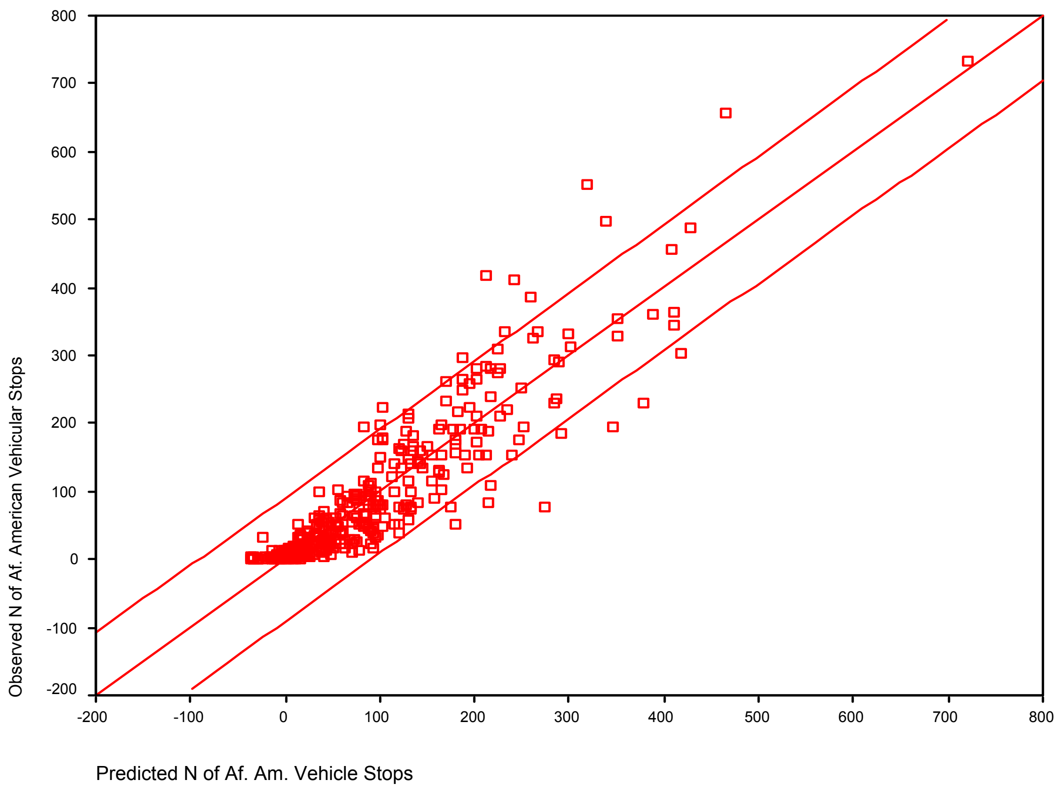
Summary of Findings for Vehicular Stops

Similar to pedestrian stops we modeled the number of vehicular stops for each census block group, as well as the number of African American vehicular stops and consent searches. African Americans made up 42.3% of the drivers of vehicles stopped (whites 51.3%). The major factors we found determining the overall number of stops of vehicles include the number of drivers in accidents and number of successful consent searches in the vehicular context. **The important predictors for the number of African American drivers stopped were the number of white drivers stopped, the resident African American population, the number of African American drivers in accidents, as well as the number of successful consent searches in the vehicular context.** We interpret these findings to mean that citizen demand is important in accounting for police presence, i.e., police are called to patrol for public safety matters where accidents occur. Further, the demographic makeup of the drivers is important (as measured by African American residency and involvement in accidents), as is the success in finding contraband.

Figure ES2 below shows the distribution of census block groups around the regression line for the number of African American drivers stopped. Again, boxes above the regression line represent areas with higher than expected numbers of African

American drivers stopped. Boxes below the regression line represent areas with fewer African Americans stopped than expected. As can be seen, some areas lie above and some below the regression line. Again, we do not know with certainty that areas above the regression line represent an "excessive" number of vehicular stops of African Americans. Likewise we cannot be certain that the linear additive model shown in the figure and assumed to reflect the command reaction to calls for service in an area adequately captures this relationship (See Appendix F for a discussion of non-additive or logged models.)

Figure ES2. Predicted and Observed Number of African American Drivers Stopped



In attempting to better understand the factors that might account for the identified positive or negative outliers, we presented a map of the outliers to police leadership of the districts involved. They suggested the following possible explanations for the positive outliers: 1) **checkpoint activity** (i.e., the location of a vehicle check point); 2) **a rash of accidents** in an area resulted in more patrolling in 2002; 3) presence of **major north-south and of east-west thoroughfares**; 4) **proximity to the coliseum**; 5) presence of a **police substation**; and 6) **"crackdown" area** where drivers are "stopped for everything" because of erratic driving.

As for the negative outliers of African American vehicular stops, the police leadership suggested: 1) prevalence of "**service roads" rather than thoroughfares**; 2) prevalence of "**dead-end" roads** (thus traffic is perceived to be limited and access to the area by the police is also limited); 3) area with predominantly **white commuters**; 4) presence of a predominantly **Asian and an Hispanic population**; and 5) presence of a large **shopping center** (with private security).

Summary of Findings on Pedestrian Consent Searches

The literature and debate on racial profiling has often centered on the searching of citizens in the context of what is called a "consent search." In a consent search the officer asks the citizen for permission to conduct a search of the person or personal belongings. Seventy-two percent of the consent searches of pedestrians were of African American.

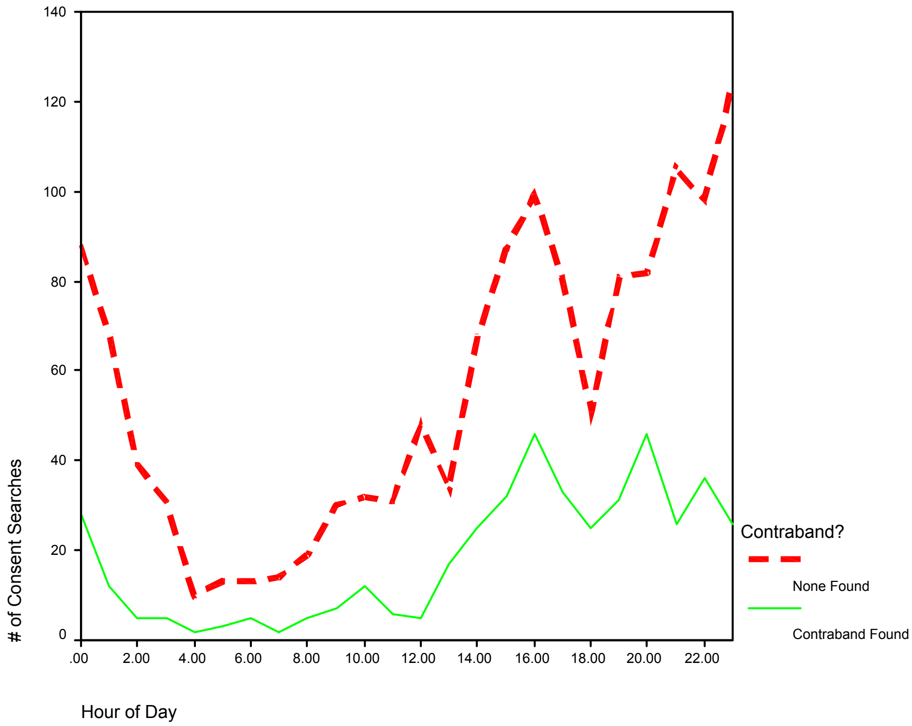
An important element in explanation of consent searches is the success rate in finding contraband. Success rates are shown to vary with the volume of consent searches. Where there are more consent searches conducted, there is less success in finding contraband. The volume of consent searches varies with the hour of the day as well as with the neighborhood context. We find that for African Americans who are consent searched in neighborhoods with relatively high levels of incivility calls for service the success rate is lower than it is for African Americans in contexts with fewer calls for service for incivility offenses. However, the success rates for whites in pedestrian consent searches in high incivility neighborhoods is even lower (11.7%) than that of African Americans.

The **inefficiency in finding contraband** (mostly drugs, but also alcohol, firearms, and drug money) **varies with the time of day**. Figure ES3 shows the success rate in finding contraband by hour of the day. Notice where there is a large distance between the two lines in Figure ES3. The relatively inefficient times of day for finding contraband are at 04:00 and late evening/early morning hours. At the same time, these same hours are the times when many successful searches for contraband occur – note the "spikes" at 16:00 and 20:00.

We identify areas of the city (census block groups) with relatively high numbers of pedestrian consent searches of African Americans relative to a statistical model in which the following factors are the most important: **number of incivility calls for service and the success rate of African American consent searches in the pedestrian context**.

The areas with the relatively high and low numbers of consent searches of African Americans appear in Figure ES4 below. Similar to the pattern we observed earlier for pedestrian stops, some areas have relatively high numbers of consent searches in the pedestrian context, while some have low numbers. Whether those areas with relatively high numbers are indicative of bias, we cannot say. It is possible that the searches in those areas can be justified by factors not included in our model, including a history of drug problems, amount of drugs seized, demand from the community for police to do searches (perhaps from local political groups), and so forth. Also, we do not claim

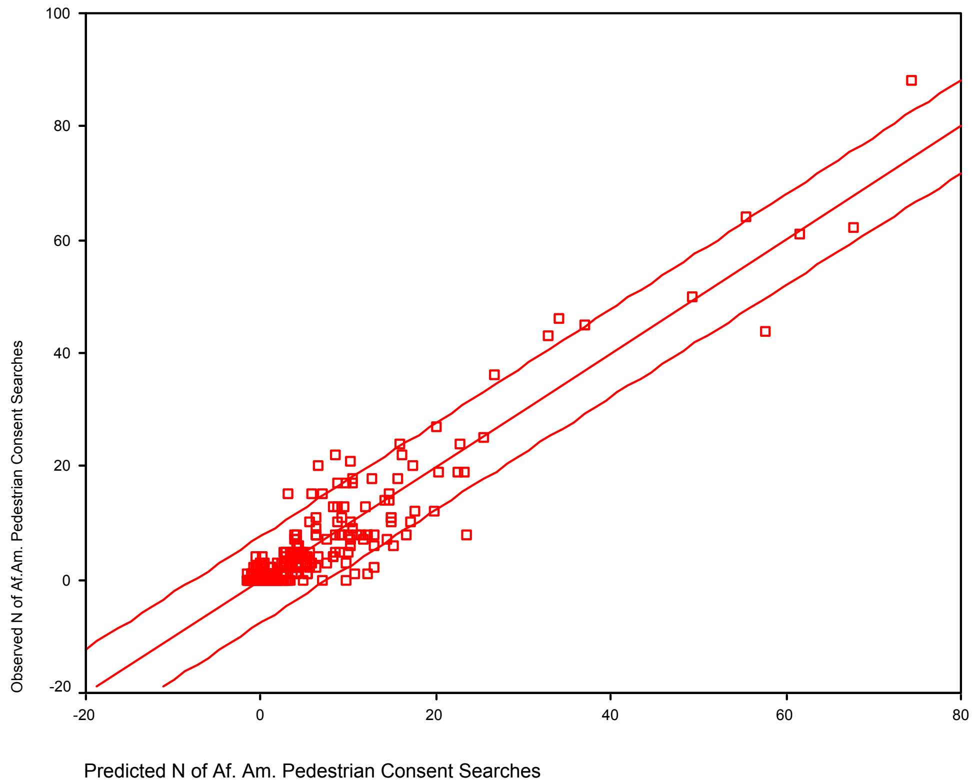
Figure ES3. Number of Consent Searches by Hour of the Day: Contraband Found or Not



that the functional form of the model (here a linear additive model) is necessarily the most appropriate form of the model – see Appendix F.

The local police leadership offered some of the same factors discussed above for outliers in the number of African American pedestrian stops to explain the outliers in searches. For African American consent searches in the pedestrian context, these additional possible explanations for the positive outliers were mentioned: 1) proliferation of **street prostitutes** in an area such that searches were often less likely to find contraband; and 2) an **aggressive drug enforcement area**. For negative outliers in African American pedestrian searches, the police leadership discussed the following:

Figure ES4. Predicted Number of African American Consent Searches in Pedestrian Context by Observed Number



1) presence of a large **cemetery**, driving down the pedestrian traffic in the area and thus lowering the number of consent searches; 2) **"lightening rod" effect** of an adjacent hot spot neighborhood that draws police resources away from nearby neighborhood areas; 3) **local shopping center with private security**; and 4) possible **underreporting of stops and searches** by some police officers.

Summary of Findings on Vehicular Consent Searches

Results for vehicular consent searches are generally similar to that found for pedestrian consent searches. African Americans constitute 64.3% of all those subjected to a consent search at a vehicular stop. When we modeled the number of African Americans stopped and consent searched per census block group, we found the following factors to be important: number of calls for service for incivility offenses and the number of vehicular stops of African Americans. (To a lesser extent, number of white vehicular consent searches, number of African American residents, African American consent search "hit rate" and age of residents are factors). Thus, unlike the models for the other outcome measures, there were several factors with effects.

We identified census block groups with relatively high and low numbers of African American consent searches in the vehicular context. Figure ES5 below shows the results of that analysis, and it identifies some areas with counts of African American consent searches well above the regression line, as well as areas well below the regression line. As was the case with the pedestrian stops above, we cannot say whether the number of consent searches here is excessive, or whether the linear additive assumptions of the model are to be preferred.

Some possible reasons for the positive outliers, as per the suggestions of the local police leadership, include **factors already mentioned** for the outliers in the above figures. As for negative consent search outliers of African Americans in the vehicular context, they mentioned: 1) presence of a **research plaza**; 2) a downtown area where searches were unlikely to be conducted due to the **heavy pedestrian traffic** on the streets; and 3) prevalence of new, small homes with many **"dead end" streets**.

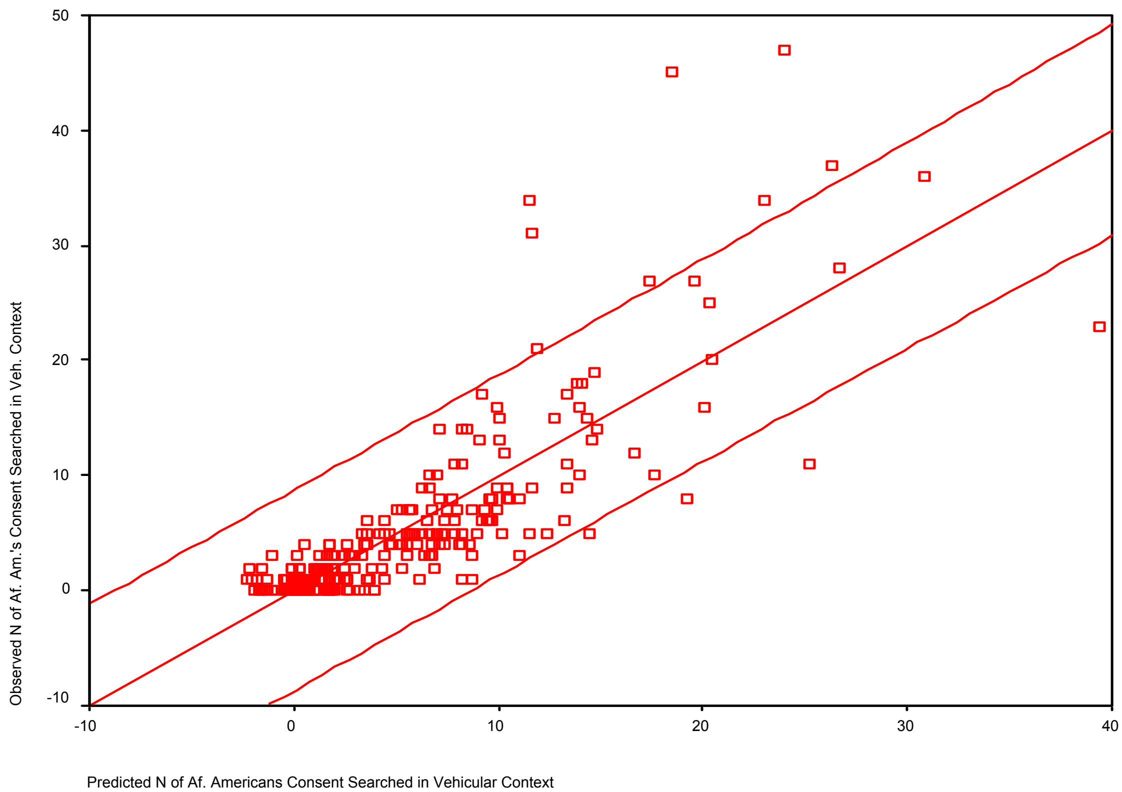
Conclusions

In general we found that **the prevalence in the number of stops of citizens in the pedestrian and in the vehicular context is not accounted for by the racial makeup of the census block groups** with which the data were analyzed. The factors that generally account for the number of stops are factors associated with the calls for service in the area, particularly **calls for "incivility" type offenses (prostitution, drugs, inebriated pedestrians, and fighting).** Also important is the **success in finding contraband**, especially drugs and alcohol. In areas **where there are more incivility calls for service and where there is more success in finding contraband, there are more pedestrian stops and searches.**

For vehicular stops, the number of drivers in accidents is the best predictor of the number of vehicular stops, but success in finding contraband in consent searches is also important. The number of incivility calls for service is not a statistically significant predictor of the number of vehicular stops. **For neither vehicular stops nor for pedestrian stops is the racial make up of the population a factor in determining the number of such stops. The number of incivility calls for service in a census block group is important for consent searches of African American drivers, as it is for pedestrian consent searches.**

That being said, the results of our analysis show that there are some areas of Charlotte where there are **more stops and more searches of African Americans than one would expect, given the factors we have identified as relevant to such police**

Figure ES5. Predicted and Observed Numbers of African American Consent Searches at Vehicle Stops, by Census Block Group



activities. At the same time, **we have found areas where the levels of stops and searches are below what our models predict**. Whether or not the degree of departure from the model's predictions represents excessively high or excessively low rates cannot be determined conclusively in this report with the available data. More information is needed. The CMPD has supplied more specific information about the areas that were identified as outliers, and we have reported them in the report (as discussed above). Such information has to do with the **history of drug problems and drug seizures** in an area, the **demand for service in an area through political organizations**, identification of the location **of hot-spots of crime,** areas targeted for **community policing** activities, and other idiosyncratic characteristics of neighborhoods. The CMPD in conjunction with the citizen advisory group of this project should discuss these factors and try to draw conclusions about whether the degree of stops and searches are excessive in specific areas such that remedial actions need to be taken.

Abstract

Data on stops of citizens by the Charlotte-Mecklenburg Police Department (CMPD) are analyzed to address the question of whether there is bias in the stopping and searching of citizens by the CMPD. Although evidence of bias is sought with regard to ethnicity, gender, and age, special focus is given to race. Throughout the analysis, stops of pedestrians are distinguished from stops of vehicles. Baselines for comparison are defined primarily in terms of police calls for service (911 calls), residency, and participation of citizens in accidents. Census block groups are chosen as the unit of analysis as opposed to larger geographic units to lessen problems associated with spatial heterogeneity. The goal of this report is to provide an empirical basis for evaluative conclusions to be drawn by the citizen advisory board for this project and the leadership of CMPD. Some areas of the city are found to have excessively high rates of stops of African Americans, while others have excessively low rates -- relative to the expectations derived from models of stop data. Whether or not these instances of stops are examples of arbitrary profiling cannot be determined conclusively from the present data. It is beyond the scope of this report to say whether the extent of the differences in the expected number of stops and searches across districts is excessive relative to the multiple goals of the CMPD (promote community safety, prevent crime, respond to calls for service, etc.). More information and evaluative judgment is necessary to claim that the extent of policing across districts is not commensurate with the need for such policing.

Introduction

The question of whether police are stopping citizens in an arbitrary manner is addressed with available data from the Charlotte-Mecklenburg Police Department. Specifically, we as researchers have been supplied with stop data recorded by the CMPD to assess whether or not there is evidence of "arbitrary profiling" as it relates to the gender, age, and race or ethnicity of the citizens in the CMPD jurisdiction. By "arbitrary profiling" it is meant that police may arbitrarily make decisions (such as stops or searches) impacting citizens based on the citizens' status as women, minorities, or age (young people).[1] The challenge we have as researchers is to determine whether or not the apparent disparities in the number of stops of citizens are in accordance with some reasonable expectation of what is an appropriate level of stops of a demographic group. That "reasonable expectation" for researchers is based on measures or baselines that we use and which stand as proxies for the true expected number of stops absent racial discrimination.[2]

We have identified several available measures that provide us with information to help judge whether a given district or area has an excessive number of stops of African Americans. We divide the corresponding analytic task into two questions: 1) the "deployment question" -- is the level of stops in an area commensurate with the types of problems called in by citizens (calls for service or 911 calls)? and 2) the disparity-in-stops question -- is the level of stops for a particular demographic group (e.g., African

[1] Specific suspects of specific crimes are stopped based on physical description, and that does not constitute profiling.
[2] The literature on direct measures of drivers behavior is limited. See Lange et al, 2001 on speeding behavior, as well as Smith et al., 2003.

Americans) commensurate with estimates of who is likely to be on the streets (driving vehicles or as pedestrians) in a particular area?

The deployment question requires that the analysis must take into consideration where police are likely to be present.[3] Presumably every area of the jurisdiction of CMPD could have police officers present at any time, but in reality police spend more time in some areas than others – either because they have been brought there by citizens who call "911" (and a dispatcher has forwarded this information such that an officer responded to the call), or because the officer is patrolling or engaged in an investigative function. The disparity-in-stops question must take into consideration the prevalence of police in a geographic area, as well as the presence of demographic groups of citizens in those areas. Put simply, the number of citizen stops in an area varies as a function of police and citizen presence.[4] Some studies have relied on residency measures (typically census data), as a proxy measure for whom the police observe. We examine residency but also include the demographic characteristics of those involved as drivers in vehicular accidents as a measure of citizen presence in a census block group. Thus, the proportion of those drivers in accidents who are African American will serve as one baseline for us to compare the proportion of those citizens stopped who are African American.

The reader should note that there are some questions that cannot be answered by the research here. We cannot say from the type of data available to us that any officer or

[3] We do not mean "deployment" to refer to the study of how many officers should be, or are, assigned to a district or "response area" on a particular day or a particular time. The CMPD uses MPP (Managing Patrol Performance), a system of software that helps in deployment decisions of that nature. We will assume that calls for service largely dictate the level of deployment of officers, an assumption that is reinforced by the fact that calls for service are highly correlated with stops.

[4] The research on possible police bias has generally not taken into consideration the likelihood that citizens' risk of being stopped by the police will vary with the degree of "exposure" to policing. The more policing in an area (the more calls for service, the more crime, the more investigations), the greater the risk of a citizen being seen by police and subject to a stop.

specific group of officers is biased in their behavior toward citizens. Nor can we say that African Americans who experience disproportionate numbers of stops in a specific geographic area do so because of racial bias. However, we can provide information in this report as to what factors determine the number of African Americans stopped in an area. These factors, we hypothesize, will be primarily measures of police presence at a location (e.g., as measured by 911 calls) and by citizen presence (as measured by demographic characteristics of drivers in accidents and of residents). We also speculate about what other factors omitted from our analysis (due to lack of measurement of these factors) might be accounting for a relatively high number of African American stops by the police. In addition we asked local police commanders what factors they thought might be missing from our models, such that areas with excessive numbers of stops (or, alternatively, too few stops) of African Americans might be accounted for. Whether corrective measures ultimately need to be taken by the CMPD to modify the nature of their interaction with citizens is beyond the scope of this report. A citizens' advisory committee, along with representatives of the CMPD, will discuss our findings, and make any necessary decisions about whether – and what – corrective measures are needed.

It should be further noted that it is not our purpose here to evaluate the general value of pedestrian stops, vehicular stops and subsequent searches on the part of the CMPD for the control of drugs or other contraband. Whether these methods are generally valuable for society or not is beyond the scope of our research. Nor do we claim that finding contraband in approximately one in four consent searches (searches in which the citizen is asked and gives consent to being searched) is a good, or acceptable ratio for the CMPD. Thus the degree of efficiency in the stop and search tactics used by the CMPD is not a matter that we pass judgment on in the current research.

To help provide a picture of what the CMPD does, two primary types of baseline measures are used in the present analysis: the number of calls for service and the demographic composition of who is likely to be on the streets and sidewalks of the jurisdiction of the CMPD (as measured by number of drivers involved in accidents in an area and who resides in an area). The first helps us address the question of whether the level or degree of policing is commensurate with the stopping and searching of citizens in an area. That is, the police generally respond to (most) calls for service and are thereby placed in specific geographic locales where citizens are at "risk" of being stopped. The second set of measures tells us who are on the streets (pedestrians and those in vehicles). For much of the analysis below, "area" will be defined as the census block group (roughly areas of the city that on average are home to about 1,800 citizens – 373 such areas in the CMPD jurisdiction). Fortunately, CMPD, which has a national reputation as a leader in the area of geographic analysis of crime, was able to provide us with data that allowed for the mapping ("geocoding") of the vast majority of the stops, accidents and calls for service studied here.[5] We use census estimates of who lives in a block group, but generally we find that evidence of "demographic presence" in the form of vehicular accidents may be the best available measure of who is in a specific area at a specific time (this will be discussed more below).

[5] By "geocoding" we are referring to linking an address or location (e.g., intersection) with geographic coordinates that allows for classification of a specific point in census block groups. Census block groups are chosen not only for their availability but because they represent a level of analysis large enough to have a statistically reliable number of observations (stops, calls for service, accidents) yet small enough to limit problems associated with "spatial heterogeneity" (a possible lack of correspondence between measured police presence and measured citizen presence).

As noted above, the deployment levels of police as they impact stops of citizens (pedestrians or those in vehicles) should be evaluated within the context of some standard of exposure to police presence. That standard, we argue, has to do with the volume of calls for service (911 calls) for particular types of offenses. Put simply, a given area may have a high number of stops simply because the police are more often present in those areas. If, somehow, the police were "over-policing" some types of neighborhoods (i.e., they are physically present more than they "should be" given the need for their services), there would probably be a greater number of stops in those neighborhoods relative to other neighborhoods. If those neighborhoods are disproportionately African American, there would appear to be racial disparity in the stops for that neighborhood. (By "over-policing" we simply mean the deployment of more officers to an area than seems necessary.)[6]

As it turns out, not all calls for service are equal. We examine empirically several types of calls for service (CFS). For both pedestrian and vehicular stops we find that calls for service for what we refer to as "incivility" calls (fights, drunks in the street, drugs, and prostitution) are important indicators of problem neighborhoods that account for a large police presence and activity level. We find that policing in the form of pedestrian and vehicular stops is largely commensurate with such calls for service, as will be shown in the analysis below. However, as also will be shown, there are several areas with excessively high -- as well as several with excessively low -- numbers of African Americans stopped. This will be addressed below.

[6] "Over-policing" implies that the assignment of officers to an area is not commensurate with the policing needs of an area. We model the need for policing in this report, but determining need fully is a complex issue that goes beyond the scope of this report. Note that we make no general claim that there is "over-policing" on the part of the CMPD.

The decision to use the census block group as the unit of analysis for this report was made not only because it was an available unit in our geographic programs (here, ArcGis), but because it had other advantages, as well. First, using smaller units allows us to study processes across geographic areas so as to have a sufficient number of observations to conduct reliable analysis. That is, we have 373 census block groups, such that our counts of stops, accidents and CFS are sufficiently large to produce reliable measures. Second, the census block groups are small enough to minimize some measurement issues that stem from the problem of "spatial heterogeneity." Such is not the case when large units of analysis are employed (such as, for example, the 12 districts of the CMPD). In a nutshell, large aggregate measures can be misleading because of variation in attributes (such as racial composition) within a geographic area. Using smaller units of analysis generally helps reduce these forms of measurement error. See Appendix I for a discussion of the potential consequences of spatial heterogeneity.

Theories of Racial Bias in Policing

Before addressing in greater detail the methodological issues that allow us to look for the presence of possible arbitrary behavior on the part of the police, it is useful to discuss some of the many theories relevant to the expectation that race could play a role in the decision making of police as individuals and as an organization. Theories vary from those that claim that racial hatred or animus guides decision making, to theories that argue that police avoid contact with certain groups (See Harris, 2002 for a review; Dovidio and Gaertner, 1986). One form of possible bias is that of cognitive bias (Gaertner and Dovidio, 2000; Devine, 1989; Bargh and Pratto, 1986; Barch, Lombardi and Higgins, 1988; Bargh, 1989, 1994). Here police officers are unaware of their own bias toward subgroups, but their behavior belies their attitudes. For example, an officer may profess no racial bias, yet the officer may look harder for signs of drugs without being consciously aware that he/she is doing so when stopping a vehicle driven by a young African American male. Cognitive bias can take many forms, including presumptions about the likelihood that a person's gender, age or race/ethnicity would makes one more "suspicious" or subject to scrutiny.

Institutional bias is a generic term for any number of department policies that may be detrimental to certain subgroups and which have no factual basis in the behavior of those subgroups (Walker et al., 2000). For example, police may decide to patrol an area near an "Hispanic bar" because in the past they have occasionally picked up drivers for DWI in that area. However, if the policy of patrolling that area is based on an ethnic stereotype, or if it is done without regard to the prevalence of accidents or other evidence of DWI, then the policy may be a form of institutional bias.[7]

Theories of No Racial Bias in Policing

In addition to theories that lead one to expect bias on the part of police, there are also theoretical reasons for expecting that the police would not act in a manner predicated on the status characteristics of the citizens. These theories, like those above, are also grounded in a broad psychological, sociological, and criminological literature.

A type of organizational theory called institutional theory states that organizations generally achieve their stated manifest goals (Meyer and Scott, 1992). Thus, the CMPD

[7] Thus, whether or not there is a conscious awareness on the part of leadership that their policies result in a disparity in policing, there is institutional bias.

largely tries to make the city and roads safer by their visibility to the public (general deterrence) and in stopping and citing violators (specific deterrence). Also, the police try to prevent crime through community policing efforts aimed at helping specific communities within the city gain or maintain control over their streets. If officers strictly pursue the mandates of their organization, racial bias should not play a role in the pursuance of the goals of the force.

Presumably there are costs to be borne by officers who engage in biased behaviors. Various theories associated with the study of organizational context share a basis in learning theory and suggest that officers who express racial bias would be negatively sanctioned (assuming a culture that is accepting of diversity) and learn to desist from such expressions (Bandura, 1969). That is, an officer who expresses openly racist comments or who brags about his/her targeting of a particular ethnic group, may suffer both informal negative sanctioning from fellow officers, or formal sanction in the form of reprimand or suspension for such behaviors. Rather than risk such costs, the officer behaves in a manner consistent with the group expectations. Relatedly, routine activity theorists (Felson, 1994) would point out that in the everyday contexts any behavior that requires "extraordinary effort" will tend to desist. Police encounter numerous citizens in the course of their day-to-day work. A racially biased officer would have to exert considerable energy, risking sanctions on an ongoing basis, to target a particular ethnic group, and that effort could be met with numerous complaints by citizens and fellow officers if he/she frequently expressed racist attitudes or behaviors. Thus, those behaviors would desist or come to represent a very small proportion of an officer's behaviors.

Empirical Evidence of Possible Bias at the Aggregate Level

With these two sets of expectations of bias or lack of bias in mind, we turn now to the two central questions regarding racial bias. First, are police deployed in an equitable manner so as not to over-police areas where African American drivers drive or citizens walk? If not, we would expect to find that the degree of policing is commensurate with the crime and traffic problems in most areas (e.g., as indicated by calls for service and participation in accidents). The level of policing could be below or above what is called for by crime and traffic problems. Second, we can identify particular areas of the city with disproportionate numbers of stops and citations issued to subgroups, such as African Americans?[8]

For much of the analysis the central demographic group of concern is African Americans. Crime rates are well known to vary by age and gender, with the younger population (teenage and young adults), as well as the male population, considerably more likely to engage in crime than older and female populations. Thus, we would expect disproportionate stops of such groups to be behavior based. While there is considerable research on the greater prevalence of certain crime types among the African American population (as reported in the National Crime Victimization Surveys every year since 1973), there is also an extensive literature on police bias in the stopping and criminal

[8] As simple as some of the analytic goals of this report seem to be – ascertaining if deployment is commensurate with the problems of an area, and determining whether particular areas have excessively high rates of police interventions of African Americans – the available data are limited such that we have no direct measures of the degree of policing nor of the exact whereabouts of the patrolling by individual officers. However, the strong correlation between the number of calls for service and the number of stops suggests that we are adequately capturing deployment for the purposes of our study.

processing of African Americans. Thus, we consider our primary concern here to sort out the policing response to the African American community.[9]

Analytic Overview

Our analysis strategy is to first examine the question of whether the number of stops in an area is commensurate with the calls for police service. Thus, we try to determine whether the degree of policing in an area is driven by demand for service rather then by the demographic characteristics of the area. If calls for service are found to be statistically determining[10] stops -- and not the race of the citizens resident or present in an area (as measured by the demographic characteristics of those drivers in accidents in an area) -- then we can assume that deployment of officers to an area is largely due to demand and not to institutional forms of bias. Of course, who is stopped may be different from whom the officers observe when they go into an area to meet demand. Presumably bias may be introduced into the process after the decision is made to enter into an area or district. Thus, it is necessary for us to proceed further in our analysis to see what factors influence specifically how many African Americans are stopped and searched in an area. As such, our methodology is two-tiered. In the first tier, we develop empirical models of the number of people who are stopped to determine if the racial composition of an area influences the decision to deploy officers to an area. Then, in the second tier of the

[9] The number of Hispanics stopped by CMPD represent a very small proportion of the stops and consequently we will not attempt to conduct a full scale analysis of stops of Hispanics in this report.
[10] By "statistically determining" we mean that there is a strong correlation, but not a perfect correlation, between the number of calls for service and the number of stops. There will be an imperfect correlation typically in any such relationship. The word "determining" thus should not imply that the number of stops is only related to the number of calls for service. Also, we do not assume that a stop typically results from a specific call for service, even for calls for service for a person suspected to be involved in an illegal behavior. Rather, we are referring to the number of calls for service in the aggregate for an entire year (2002) as it correlates with the number of stops in the aggregate in that same year.

analysis, we study what factors influence the number of African Americans who are stopped. Here, presumably, the calls for service will again be important, but so might the racial makeup of an area, as well as of the race of those estimated to be present as evident by accident data. All these factors could legitimately play a role in determining how many African Americans are stopped (either stopped in vehicles or as pedestrians). After determining what factors predict the number of African Americans stopped, we then look to see whether some areas lie above or below the expectations of the empirical model. The "positive outliers" will be areas with "too many" African Americans stopped, relative to the model's predictions. The "negative outliers" will be areas with "too few" African Americans stopped. These positive and negative outliers were then shared with district commanders, and possible reasons for their status as outliers were discussed.[11] These discussions are summarized in the report below.

Calls for Service

The question of whether a given area has an appropriate number of police officers assigned to it is relevant to the question of "arbitrary profiling" because if too many officers are deployed to some areas over others, then those areas would be more likely to have an officer witness an offense or more likely to have an officer stop a pedestrian or a vehicle that they think is suspicious. If those neighborhoods are populated by a disproportionate number of African Americans, then deployment might be accounting for the disparity in city-wide statistics. Thus, an important question is whether the

[11] A meeting was held Dec. 19, 2003 in Charlotte with researchers and various district commanders and those familiar with the outlier districts identified.

deployment to an area can be accounted for by legitimate reasons or whether there is bias involved.[12]

Calls for service data represent an important source of information on the need for policing in an area. Both the volume of calls and the types of calls are likely to be relevant in determining how much police activity we should expect to find. Calls for service data (911 data) are complicated, however, because many of the calls for service in the data base are actually calls initiated by the police. If the police witness a crime, for example, they are expected to call 911 so that the dispatcher does not needlessly dispatch another officer to the scene (if someone else reports the same incident).[13] These appear as "officer initiated" calls in Table 1 below. As can be seen in the table, the most common type of 911calls are from citizens and are calls that require an immediate police response (71.2%) with another 6.2% also from citizens but classified as "non-essential" – minor problems that require no immediate response by the police.

Table 1 Calls for Service by Origin of Call

Originating Source	Number of Calls	Percentage of All Calls
Citizen Initiated	237,674	71.2%
Non--Emergency Police Services (NEPS)	20,546	6.2%
Calls with No Officers Assigned	33,622	10.1%
Officer Initiated Calls	35,233	10.6%
Other	6,605	2%

[12] Of course, a "seemingly high" rate of stops of African Americans is probably based on the proportion of residents who are African American, which is probably in most instances a poor baseline against which to compare rates.
[13] Also the 911 data base serves as a summary of crime and other problems in the city, so a complete accounting of such would require that the police report offenses that they are witness to.

Responses to the citizen initiatives are defined by the 911 dispatcher into three priority groups: Immediate, Emergency, and Routine. Emergency responses require rapid response to the location (possibly with a siren, flashing lights), whereas Immediate means that the officer responding will typically drive to the location as a normal driver (e.g., within speed limits, stopping for lights, etc.). Routine response would refer to a response often at a later time, convenient for the officer.

In Table 2 we show the relationship between the type of calls for service (citizen initiated, etc.) and the type of response given. As can bee seen in the table, generally the average citizen call is responded to with an "immediate" response (70.3% of the citizen initiated calls where an officer is required). Only in 6.5% of the citizen initiated calls is there an "emergency" response. There is considerable variation in the number of calls for service and in the number of emergency calls for service across districts (Table 3). Note that many of the pedestrian stops occur in District D, which is proximate to downtown Charlotte. Parts of District B and C are also proximate to the downtown area. (Across most U. S. cities, crime rates are generally high for areas in or proximate to downtown.)

However, because districts vary in size -- with areas away from the center of the city being relatively large compared to areas closer to center city -- and also because each district varies internally in its demographic makeup, as well as in the prevalence of crime (See again Table 3), it is more useful to use a different unit of measurement of the geographic areas within the jurisdiction of the CMPD.[14] The large

[14] See Smith et al, 2000 for a discussion of the value of small units of aggregation.

Table 2. Category of Call for Service by Type of Response

		Category of Call for Service					Total
Priority		1. Citizen Initiated	2. Non-Essential Police Services	3. Officer Initiated	4. No Officer Assigned*	5. Other	
Emergency	Count	15500	3	58	905	431	16897
	% within PRIORITY	91.7%	.0%	.3%	5.4%	2.6%	100.0%
	% within CATEGORY	6.5%	.0%	.2%	2.7%	6.5%	5.1%
Immediate	Count	166988	7	22334	31136	4738	225203
	% within PRIORITY	74.1%	.0%	9.9%	13.8%	2.1%	100.0%
	% within CATEGORY	70.3%	.0%	63.4%	92.6%	71.7%	67.5%
Routine	Count	55174	20536	12841	1580	1432	91563
	% within PRIORITY	60.3%	22.4%	14.0%	1.7%	1.6%	100.0%
	% within CATEGORY	23.2%	100.0%	36.4%	4.7%	21.7%	27.4%
Unknown	Count	12	0	0	1	4	17
	% within PRIORITY	70.6%	.0%	.0%	5.9%	23.5%	100.0%
	% within CATEGORY	.0%	.0%	.0%	.0%	.1%	.0%
Total	Count	237674	20546	35233	33622	6605	333680
	% within PRIORITY	71.2%	6.2%	10.6%	10.1%	2.0%	100.0%
	% within CATEGORY	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
*Includes Duplicate Calls							

size of the CMPD districts can mask much of the variation in citizens' behaviors and police response. For example, crimes are typically concentrated in some areas and not others. So called "hot spots" of crime could be a single street address or a city block (Sherman et al., 1989). There is presumably much variation within large districts, such as the 12 police districts of CMPD. For example, the number of hot spots, and the demographic make up will vary within districts. To improve the precision of our measurements, we looked to find a smaller geographic unit of analysis to minimize what is called the "spatial heterogeneity" problem within geographic areas (again, see further discussion in Appendix I). In essence the specific heterogeneity problem that we are referring to here is a possible mismatch between our measures of where policing is occurring and our measures of where citizen misbehaviors (or suspicious actions or circumstances) are occurring. For example, if we were to use residency demographics, the assumption of a standard analysis of possible police racial bias is that the degree of policing and the percentage of African Americans within a district are evenly distributed spatially across the entire district. Thus, a measure such as the percentage African American resident in an area and the percent stopped or cited, should be approximately equal. Since past research shows that African Americans and whites in the American context tend to be racially segregated in their residency patterns, it is unlikely that there would be an "even" distribution of the races across all sub-areas of a district. Rather, there will tend to be "pockets" of blacks and "pockets" of whites within larger areas. Nor will policing be evenly distributed. The "mismatch" of citizen and police presence may attenuate the coefficients in our models of these processes.

With smaller areas, such as the census block groups that we use in the current analyses, we maintain that there will be greater homogeneity to the distribution of demographic and other characteristics (including crime) within an area than there would be using larger units of analysis.

We have chosen to use census block groups (sub-areas of census tracts) as a meaningful unit of analysis for comparisons.[15] Census block groups, which average about 1,800 citizens per block group, are even more likely to show variation across areas than are CMPD districts because the latter are designed to be similar in workload,

[15] There are few convenient alternatives. Census tracts are also quite large, and census blocks are too small for meaningful analysis.

whereas the former are not. Indeed, we found that 98 census block groups -- out of 373 -- had no pedestrian stops in 2002. This suggested to us that these are largely low crime residential areas. Also, block groups may correspond more naturally to communities that exist within the CMPD jurisdiction. Thus, census block groups might be more homogeneous with regards to income and race of residents. There are 373 block groups in the Charlotte-Mecklenburg area (371 of which we have calls-for-service data). Comparing the percent of all emergency and immediate calls for service across the 373 block groups, we find that they vary from zero percent to 37.5%, with a median value of about 7%. Thus, some areas generate substantially more emergency calls for service than others.

To accomplish the task of evaluating the relationships among the various data bases (stops, calls for service, and accident data), we geocoded the addresses of these events ("geocode" means that we identify the geographic coordinates of the specific location of each of these types of events). The resulting data bases (which omit some observations due to inaccuracies in the addresses or other factors) were used for much of the analysis below. (See Appendix C for a comparison of the geocoded versus the full data bases). The data bases used in the analysis here include a representative sample of those in the full data base.

There is also variation in the reasons for the calls for service. One would generally expect that serious crimes against persons (crimes of serious violence), as well as the more common, serious property crimes, would lead to more calls for service and resultant policing of areas. Also, in light of efforts to engage in community policing (in

Table 3 Pedestrian Stops by District

CMPD District	Frequency	Valid Percent	Cumulative Percent
Valid			
A1	284	5.0	5.0
A2	397	7.0	12.1
A3	271	4.8	16.9
A4*	3	.1	16.9
B1	355	6.3	23.2
B2	114	2.0	25.2
B3	289	5.1	30.3
B4*	3	.1	30.4
C1	376	6.7	37.1
C2	431	7.6	44.7
C3	494	8.7	53.4
C4*	37	.7	54.1
D1	493	8.7	62.8
D2	1464	25.9	88.7
D3	637	11.3	100.0
Total	5649	100.0	
*A4, B4, and C4 Are administrative, or non-geographic designations.			

part community policing tries to prevent crime and protect citizens in the more highly vulnerable neighborhoods), we also suspect that some crimes traditionally seen as less serious may be drawing the attention of police (for example, calls for service for drugs, prostitution, fights, and intoxicated pedestrians). Thus, three types of calls for service that are relevant to our subsequent analysis are calls for 1) violent/serious crimes (kidnapping/abduction, armed robbery from business, armed robbery from person, weapon, shots fired/armed subject, or rape/sexual assault), 2) break and entry of residencies and of businesses; and 3) incivility type offenses, such as those just mentioned. All three of these types of calls for service, we hypothesize, would presumably elicit more immediate concern and quicker police attention than others, such as parking problems, larceny, or stolen checks. We are especially interested in so called "incivility" complaints, such as prostitution, drugs, fights (non-domestic), and intoxicated pedestrians, as these neighborhoods are often where control processes are difficult to maintain and are, in some cases, deteriorating, resulting in appeals to the police to help maintain order. Moreover, we suspect that such neighborhoods with high incivility type complaints would generate more pedestrian stops and pedestrian searches than other neighborhoods.

Block groups vary from zero to 373 in the number of calls for service for incivility type offenses, with a rather low median value of 12.3 such complaints in 2002. There is a small subset of block groups with high numbers of such calls. Block groups also vary in the number of violent/serious crime complaints: zero to 281, with a median value of 40 such calls in 2002. We hypothesize that the number of pedestrian stops would be higher in neighborhoods with high incivility calls and also higher in high violent/serious crime neighborhoods, relative to other neighborhoods.

Modeling Number of Pedestrian Stops

We begin with an analysis of pedestrian stops conducted by the CMPD. Pedestrian stops are of much concern regarding the issues of arbitrary profiling because, typically, the race, sex, and age of the citizen are known before a decision is made to stop a pedestrian (whereas, in the case of vehicular stops, many times – probably most – these attributes of drivers are not as certain prior to the decision to stop a vehicle). Because of the visibility of the citizens in the pedestrian context, there is more opportunity for bias to be manifested. Also, we expect that pedestrian stops will be more a reflection of the residents who live in the areas where the pedestrian searches occur than are the vehicular stops. As part of this research project, we rode along with officers in various part of the city of Charlotte and saw first hand that stops of citizens on the streets is in part a function of where "drug areas" or "crack houses" are located. That is, if an area is well known for having locations where drugs are distributed, there are often suspicious people "hanging out." The police may decide to talk to, and eventually request a search of, some of these people as part of their mandate to control the distribution of illegal substances.

Pedestrian searches, we found, are more concentrated than are vehicular searches, in part because of the specific targeting of areas with a history of drug sales and drug arrests. As such, it is important to document that the choice of areas where pedestrian stops are more prevalent are areas that indeed have high levels of drugs and drug related calls for service (such as violent crime). If areas with, say, high concentrations of African Americans receive the most deployed patrols, but these neighborhoods are not the neighborhoods with the more severe drug problems, then arguably some form of racial profiling may be occurring. Below we will examine the extent to which some neighborhoods receive more police attention and whether it may be accounted for by the types of calls-for-service in those areas.

The number of pedestrian stops in a block group should reflect in part the volume of crime as well as crime-related activities in a block group. Block group characteristics that we hypothesize to be relevant to pedestrian searches would include the demand for service, as measured by the number of calls for service. Such a measure, however, is likely to be a crude index of the full extent of problems since presumably the police would patrol some neighborhoods with certain types of crime problems more than others.

Moreover, the degree of patrolling is not necessarily a linear or additive function of the number of calls for service. For example, neighborhoods characterized by a high rate of calls for robbery offenses or for other crimes of serious violence might be more heavily patrolled (with stops of pedestrians occurring as part of the patrolling) than the number of calls for service alone would indicate as necessary -- simply because the relatively serious nature of the crimes might require greater police presence than the number of complaints would dictate.[16] "Serious" may be defined as harmful to an individual victim or it may be defined as harmful to an entire neighborhood.[17]

Neighborhoods might be patrolled more if there are problems with street trafficking in drugs (as indicated by calls for service having to do with drugs), prostitution (usually street prostitution), intoxicated pedestrians, fights, etc. As indicated above, we refer to the latter type of neighborhood as one with a high rate of "incivilities" -- perhaps a reflection of low levels of community social control in those areas (Sampson et al., 1997). In recent years police forces in many municipalities, including Charlotte, have made efforts to provide "community policing" and have added "patrol-time" to some deteriorated neighborhoods with the visible signs of drug trafficking, street prostitution, and related activities. Thus, we might find that there is more policing in high incivility areas than would be expected if policing varied strictly as a ratio of the presenting problems.

As an initial test of the volume of pedestrian stops in a block group, we examine several characteristics of the demand for police service as measured by 911 calls of

[16] Technically, the greater police presence is simply a non-additive function of the prevalence of certain calls for service.
[17] For example, street prostitution may not be deemed as a serious offense relative to offenses such as robbery and burglary. However, from the point of view of controlling the mechanisms that bring about community decline, controlling street prostitution is often considered an important element of law enforcement.

various types. The characteristics correlated with the number of stops in a block group are listed in Table 4 below.[18] The variables listed include the following measures at the block group level: 1) number of pedestrian stops; 2) number of drivers reported in traffic accidents (sum of the number of vehicles involved in accidents and reported to authorities); 3) number of violent crimes reported by citizens in 911 calls (kidnapping, armed robbery from business, armed robbery of person, weapon offense, armed subject, shots fired, and rape or sexual assault); 4) number of "incivility" offenses reported by citizens in 911 calls (prostitution, fights, intoxicated pedestrians, and drug related calls);[19] 5) number of break and entry calls for service by citizens (of residencies and of businesses); 6) number of residents 7) number of calls by citizens regarding disabled vehicles; 8) number of hit and run calls by citizens; 9) number of African Americans residents (from census records) ; 10) number of African Americans involved in accidents as drivers (from North Carolina's Department of Motor Vehicles records); 11) number of white residents (census); 12) number of white drivers in accidents (as drivers -- NCDMV); 13) number of successful consent searches (in which drugs or alcohol was found).[20] Note that we restrict the calls-for-service variables to only calls for service

[18] In an earlier draft of this report we included the number of owner occupied households as a variable, but in the subsequent models it was not found to have an independent effect. In the rewriting of the draft we added the number of successful consent searches in which drugs or alcohol were found and now include that in the correlation matrix shown in Table 4.

[19] We selected these four items from the list of all types of calls for service – roughly 100 categories are used in the 911 data base. Calls for "suspicious persons" might also be considered an indicator of incivilities, but we found that including it did not add to the predictive success of the models. Also, we thought the presence of perceived "suspicious persons" would be rather widespread across the city and not necessarily an indication of a socially disorganized neighborhood (here we are not distinguishing between a socially disorganized neighborhood and one with incivilities).

[20] Thus we dropped successful consent searches in which weapons and money were found (the latter is relatively rare). We dropped these items because a regression analysis in which these items were entered individually revealed that they did not add to the explained variance of the model. Note that we omit an extended discussion of why these specific items were chosen. From all the approximately 100 types of calls for service coded in the 911 data base, these seemed to us to be the more likely correlates of policing activity (patrolling and stopping of pedestrians or vehicles).

Table 4. Correlations Among Variables: Number of Pedestrian Stops and Other Characteristics of Block Groups (N=278)

	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.# Pedestrian Stops	.35	.53	.77	.38	-.03	.19	.51	.31	.46	-.25	.25	.82
2. # Drivers in Accidents		.38	.41	.41	.23	.64	.74	.24	.92	.08	.95	.25
3. # Violent Offense Calls			.77	.80	.20	.23	.58	.72	.56	-.28	.17	.49
4. # Incivility Calls				.59	-.01	.23	.58	.48	.56	-.32	.25	.77
5. # Break and Entry Calls					.42	.27	.58	.73	.54	-.04	.23	.38
6. # Residents						.06	.23	.42	.14	.82	.23	-.03
7. # Disabled Vehicle Calls							.61	.10	.63	-.02	.58	.12
8. # Hit and Run Calls								.34	.76	-.01	.60	.35
9. # Af. American Residents									.42	-.16	.06	.39
10. # Af. American Drivers in Accidents										-.12	.75	.36
11. # White Residents											.21	-.23
12. # White Drivers in Accidents												.17
13. # Successful Searches												

initiated by citizens. Thus, we use a truly independent measure (independent of policing activity) of the extent of the demand for police services in the block group areas.[21]

Note that we have included some measures associated with vehicular traffic, specifically the calls for disabled vehicles, hit and run, and involvement in accidents. This is in part because we assume that the pedestrians on the streets of a block group will not only vary as a function of the composition of the residents of an area, but also vary as a function of who is driving into an area. Moreover, the volume of vehicular traffic probably is correlated with the pedestrian traffic (e.g., people driving into a commercial district park their vehicles and walk to the places they need to go).

In Table 4 above, based on 278 block groups, [22] note that all of the correlation coefficients of .12 (absolute value) or greater are statistically significant at the .05 level. The characteristic of the block groups that is most highly correlated with the number of stops of pedestrians is the number of successful searches in which drugs or alcohol was found (.82), followed by the correlation with number of incivility calls for service (.77). Thus, it seems that the police tend to conduct pedestrian stops where they have been successful in finding contraband and where they are called to respond to incivility calls for service.[23] Note that incivility calls for service, more so than serious crime, bring about policing in the form of pedestrian stops.

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[21] We tested some additional factors including the number of Hispanics across block groups. We did not find the latter to be statistically significant in our models, and we have dropped it from consideration here to simplify the discussion. An alternate measure of incivilities that included the original measure plus the number of suspicious persons calls resulted in somewhat lower explained variance than a model with the incivility measure used here – see the next table, Table 5a.

[22] Note that 371 districts have 911 data but only 278 have any pedestrian stops, so we have dropped block groups with no pedestrian stops. Models with all 371 districts included in the analysis and with the number of pedestrian stops coded to zero, produces almost identical results and have no substantively different findings than the models reported here.

[23] While it is not surprising that the number of successful consent searches resulting from a pedestrian stop is related to the number of pedestrian stops, it could be argued that the correlation is partly spurious because there must be a stop for there to be a successful consent search, thus making a positive correlation

The variable with the third highest correlation (.53) with the number of pedestrian stops is the number of drivers in accidents. This variable partly indicates the amount of traffic in a block group. Some block groups have more major thoroughfares passing through them than others, bringing more people to the block group. Presumably many of these are pedestrians.

The variable with the fourth highest correlation (.51) is the number of calls for service for hit and run incidents. We suspect that where there is more vehicular traffic there are more people on the streets, and thus more stops of pedestrians. Although the number of calls for "hit and run" incidents is not large, they may indicate the presence of drivers who are especially reckless or perhaps intoxicated. The fifth highest correlation with the number of stops of pedestrians is the number of African Americans involved in accidents as drivers, .46. This measure is assumed an additional measure of the presence of African Americans in the block groups as opposed to a measure of behavior (the other measure of presence is the number of African Americans resident in the block group, which correlates .31 with the number of pedestrian stops). Some might argue (e.g., Gottfredson and Hirschi, 1990) that the accident-prone are also crime prone, but we make no such argument here. Rather we are simply trying to measure who is more likely to be present as pedestrians in an area. We maintain that "drivers in accidents" also gives us an indication of pedestrian presence (as well as of vehicular presence). The high correlation here is suggestive of the possibility that many of the pedestrian stops are of African Americans (most, in fact, are), but we only know from the correlation that there tends to be many pedestrian stops where there are many African Americans present as

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more likely between these to variables than between other variables in the table and the number of pedestrian stops. See Appendix G below for an extended discussion of this question and related issues on the use of use of regression models in the analysis below.

indicated by their involvement in accidents as drivers, and to a lesser extent as residents in the area.

We will not discuss here all of the correlations in Table 4, but note the importance of the column of correlation coefficients for variable 10, number of African American drivers in accidents. In block groups where there are many African American drivers, (as opposed to residents, as per variable 9), we find higher correlations with the number of calls for service for incivility calls (.56), and vehicle-related calls (disabled vehicles and hit/run calls, .63 and .76, respectively) than we find between the variable number of African Americans residents and each of these three variables (.48, .10, .34, respectively). At the same time the variable measuring the number of African American residents is more highly correlated with number of break and entry calls for service by citizens (.73 versus .54). Thus, it would be unwise to dismiss residency baseline measures as unimportant since African American residency is more highly correlated than accident involvement with break and entry calls for service.

One of the central questions of our research can be addressed with these data. Specifically, we can address whether the characteristics of the calls for service in the area are better predictors than the demographic characteristics (race) of the area. To examine this question, we could enter all of the variables into a regression equation. This procedure would allow us to see what characteristics of the block groups are predictive of the number of pedestrian stops, independent of the effects of the other variables in the equation. However, some of the variables measuring characteristics of the block groups are too highly correlated with other characteristics to provide a unique and independent measure of the effect that can be reliably assessed. For example, the number of drivers in accidents is too highly correlated with both the number of African American drivers in accidents and with the number of white drivers in accidents to allow for an independent measure of the effects of all three variables while controlling for the other two variables in the same model. As a result of this "multi-collinearity" -- excessively high inter-correlations among the independent variables in the model -- some variables had to be dropped from the equation (see relevant footnotes below). Further details on some of the methodological issues in using regression analysis are discussed in Appendix G.

In Table 5a below we show a model that represents the results of a regression equation where the number of pedestrian stops in a block group is the dependent variable. The logic of our design is simple: more pedestrian stops are to be expected in block groups with higher levels (higher counts) of calls for service, residency, drivers in accidents, etc. In Table 5a we show the variables that have statistically significant effects on the dependent variable -- the number of pedestrian stops in the census block groups. All the variables from the list in Table 4 (except for the 13th variable listed, success of pedestrian consent searches – see discussion below) were tested in a forward selection procedure in which variables are entered one at a time with the variable with the highest correlation with the dependent variable entered first.[24] Then the variable with the highest partial correlation (the correlation with the dependent variable when the first variable is controlled for in the equation) is entered next. The third variable -- the one with the highest partial correlation with the dependent variable when controlling for the first two variables -- is then entered. This procedure is followed until all of the statistically

[24] In addition we tested variables such as the number of calls for service, the number of emergency calls for service, and the number of immediate calls for service, but they are highly correlated with some of the other call-for-service variables, and thus we omit further use or discussion of these variables. Also, the number of Hispanics was included initially, but found to be statistically insignificant and was dropped. Other call for service variables included in early models include calls for robbery and for assault, but these too had collinearity problems.

significant variables (at .05 probability level) are included. Omitted from the final model are all statistically insignificant variables, as well as any variables that are too highly correlated with the variables already in the equation (see Appendix G for further discussion of the method used here).[25]

The results of the forward selection model are presented in Table 5a.[26] Note that we have omitted the 13th variable, number of successful consent searches in which drugs/alcohol were found, because of complexities in this variable that will be discussed below when we examine Table 5b. We will examine Table 5a in greater detail than subsequent tables so that we can explain what some of the statistical evidence means.

Three variables were found to be statistically significant, explaining 61.6%[27] of the variance in the number of pedestrian stops across census block groups: the number of calls-for-service for incivility offenses (each call for service elicits on average .793 of a pedestrian stop – see column headed with a "B" under "Unstandardized Coefficients"), while each call for a "hit and run" results in an average of .314 pedestrian stops more stops. Somewhat surprisingly, violent offense calls-for-service actually reduce the number of pedestrian stops by an average of -.159, net of the effects of the other variables in the model. This is probably a reflection of the possibility that violent crime is made up of robbery offenses, and robbery victims may be targeted across many areas

[25] Variables with excessive collinearity that were excluded were variables with less specific information. For example, the number of drivers in accidents would be dropped rather than number of African Americans in accidents.
[26] Some of the variables in the analysis were found to have a few extreme outliers – cases that stood out from the rest of the observations. In some cases these have been Windsorized – reduced to a value consistent with the next lower value that was not judged to be an extreme outlier – see Dixon and Massey, 1969:330. Windsorizing the variable generally lowered some of the regression coefficients but did not result in any variable being changed as to statistical significance.
[27] The explained variances presented in this report are all adjusted R^2 values, unless stated otherwise. An adjusted value takes into consideration the number of independent variables in the equation and will be somewhat lower than an unadjusted. All else being equal, the larger the number of independent variables in an equation, the larger the unadjusted R^2 will be, so an adjustment is made to the R^2 statistic.

of the city, not just "problem neighborhoods".[28] Note that the effects discussed in the models represent average impacts. That is, pedestrian stops may or may not occur as a result of an individual call (i.e., a specific 911 call comes in and the police stop someone). Rather there is a "statistical" relationship referred to here in our models, implying that on average a single call for service for an incivility offense will result in .8 pedestrian stops (stated another way, for every 10 incivility calls for service, on average 8 pedestrian stops occur). Note also that we refer to the model represented in Table 5a as a "deployment" model since all of the measures in the model are of calls for service for which -- in the vast majority of cases (as per the discussion above) -- an officer is dispatched to the scene. Thus, the measures are essentially indicators of the level of police presence in a census block group (thus we refer to this model as a "deployment" model).[29]

Other coefficients in the table include the standard error, which is an estimate of the degree to which the B value (unstandardized regression coefficient) will vary if we were to repeatedly draw samples of our data. These hypothetical Bs from repeated samples will approximate a normal distribution. We can calculate the 95% confidence interval around the B presented here for number of incivilities, for example, as +/- 1.96*.058. Thus 95% of the time the sample estimate will lie between .679 and .907.

[28] For example, some robbery victims are in more affluent areas or in business areas which do not rank highly on the incivility rankings.

[29] Deployment of officers to a district (for many reasons and not only for the sake of conducting pedestrian stops) is due to potentially many more factors than those in the model of pedestrian stops shown here. The items in our model are sufficient to account for most of the pedestrian stops. The CMPD use Managing Patrol Performance (MPP) software to determine how many officers should be on duty or call for a particular police district. We refer to "deployment" here to be more specifically the presence of police in census block groups for the purpose of being available to conduct pedestrian stops. We are equating calls for service of the type studied here with police presence. Moreover, due to the nature of incivility calls for service, a pedestrian stop is a likely outcome of such a call for service due to the nature of such calls by the citizenry: drunkenness, prostitution, suspicion of drugs, and fighting. That is, it is quite likely that a pedestrian will be searched as a result of such calls for service.

Table 5a. "Deployment" Model: Number of Pedestrians Stopped by Calls for Service Characteristics of the Block Group, Statistically Significant Variables Only

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
Adj. R^2=61.6%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-.251	1.893		-.133	.895		
# Violent Offense Calls-for-Service	-.159	.069	-.131	-2.315	.021	.431	2.319
# Incivility Calls-for-Service	.793	.058	.783	13.697	.000	.425	2.351
# Hit and Run Calls for Service	.314	.085	.166	3.689	.000	.687	1.456

Also reported in the table are standardized coefficients, which can be useful for comparing the relative impacts of variables with different variances. The standardized coefficient is equal to the unstandardized coefficient multiplied by the ratio of the standard deviation (average variation) of the independent variable to the standard deviation of the dependent variable. Here we see that the standardized coefficient for number of incivilities is by far the largest coefficient, .783, relative to the other coefficients reported. **This indicates that calls for incivility offenses -- of all the variables in the equation -- are most responsible in accounting for the number of pedestrian stops in a block group.**

Further statistics reported in the table include the t-values and significance level of the test for whether the coefficients are statistically different from zero (i.e., if a B coefficient is significant, we can rule out that there is no relationship between the independent and dependent variable while controlling statistically for the other variables in the model). The t value is simply the ratio of the B coefficient over the standard error of B. For example, if you divide .793 by .058 you obtain 13.697 (see Table 5a).[30] The two-tailed significance level is also reported (here we interpret any significance value at or below .05 as meeting our criteria of being statistically significant).

Finally, we report on the extent to which the regression coefficients might be varying as a function of high correlations with other variables in the model. The tolerance is a measure of the unexplained variance in an independent variable when the other independent variables are used to predict the values of the first independent variable. In general it is recommended that values of .25 or higher be found (Belsley, 1991). The values reported in the table are well above .25. Also shown is the Variance Inflation Factor (VIF), which is simply the reciprocal of the tolerance. Values below 4.0 are considered acceptable (the inverse of a .25 tolerance). In short, the degree of correlation among the independent variables reported here is considered acceptable by standard criteria.

We interpret the results of Table 5a to indicate that the important factors in determining whether the CMPD conduct pedestrian stops in an area to be largely a function of the types of crimes that citizens report in their 911 calls. **Notably absent from the model are race variables, such as the number of African Americans in residency in the block group, or the number of African Americans who are drivers in accidents occurring within the block group.** These variables are not statistically significant, **indicating that race per se provides no independent influence on the number of pedestrian stops.**

[30] Rounding results in a slightly different coefficient (13.672) than reported here and in the table.

Alternate Model of Number of Pedestrian Stops

In Table 5b we have included the same variables as in Table 5a, but have included an additional variable, the number of successful consent searches in which drugs or alcohol was found. Note that the explained variance in the model increases to 80.4%. Also the standardized Beta value for number of incivility calls-for-service is smaller than in Table 5a (.458 compared to .783 in Table 5a), due to the inclusion of the variable measuring the number of successful consent searches. Thus, when we include a measure of successful pedestrian consent searches, our ability to predict the number of pedestrian stops is greatly increased (R^2 increases from 60.1% to 80.4%). However, as we discuss in greater detail in Appendix G, there is some spuriousness to this increase in predictability of the number of pedestrian stops since there must be a pedestrian stop for there to be a successful pedestrian stop consent search.[31] We include the variable, however, because it seems theoretically important to decision making processes involved in making a pedestrian stop: pedestrian stops would seem to be more likely to occur in areas where there has been successful pedestrian consent searches. Ideally, a measure of past success from an earlier time period, would be preferable, but such data are unavailable (again see Appendix G for further discussion of the consequences of including this variable).

We interpret the results of Table 5b to mean that pedestrian stops are largely accounted for by two factors: **demand** (number of calls for service for incivility offenses) and **success** (number of successful consent searches in which drugs/alcohol are found).

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[31] However, this is not to imply that there are a similar number of stops of pedestrians as there are successful consent searches. On average each census block group has 2.75 successful pedestrian consent searches in 2002 (in which drugs or alcohol are found), out of an average of 20 pedestrian stops. Across census block areas, however, there is a high correlation between these two variables (.82).

Table 5b. Alternate "Deployment" Model: Number of Pedestrians Stopped by Calls for Service Characteristics of the Block Group and Number of Successful Pedestrian Consent Searches, Statistically Significant Variables Only

	Unstandardized Coefficients		Standardized Coefficients	T	Sig.	Collinearity Statistics	
Adj. R^2 = 80.4%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-1.527	1.355		-1.127	.261		
# Incivility Calls-for-Service	.464	.046	.458	10.066	.000	.343	2.917
# Violent Offense Calls-for-Service	-.191	.049	-.158	-3.885	.000	.431	2.323
# Hit and Run Calls for Service	.295	.061	.156	4.844	.000	.687	1.456
# Successful Pedestrian Consent Searches (Alcohol or Drugs)	3.944	.243	.556	16.204	.000	.603	1.658

The other two variables add somewhat to the predictability of the model, but the two variables measuring demand and success account for 78% of the variance explained (this model was tested separately and the results are not shown here). In other words, the variables measuring the number of hit and run and the number of violent offense calls for service add only 2% to the explained variance.

It should also be noted that our models of number of pedestrian stops are based on the assumption that the number of stops should be a linear, additive function of the demand and success variables. This may not be a reasonable assumption. For example, it may be that there should be more of a police response with greater demand and success. A model with logged values of the dependent variable, for example, might be a reasonable alternative model. Such models are discussed in Appendix F.

Further Policy Implications of the Model of Number of Pedestrian Stops

The model in Table 5b may be used to help address the question of how to monitor future police pedestrian searches. The CMPD could rather easily monitor whether the number of pedestrian stops is normal or "appropriate" in an area by simply looking at 911 calls for incivility offenses (roughly two such calls should result in a pedestrian stop), and success rates of consent searches over a time period for an area (for a successful consent search in which drugs or alcohol is found, there could be four pedestrian stops.) If more pedestrian stops occur than indicated by demand and success, then there should be some justification for the excess pedestrian stops. If too few pedestrian stops are occurring, then there should be an explanation for that also.[32]

Racial Factors in Predicting Number of Pedestrian Stops?

To highlight the point that the racial composition of a census block group is not a statistically significant predictor of the number of pedestrian stops, we enter the two race-based measures of number of African American residents and number of African American drivers in accidents[33] into the equation in Table 5b and report it in Table 6. The results show that, indeed, these variables -- while having sufficient independence from the other independent variables to produce reliable regression coefficients -- do not have a statistically significant relationship with the number of pedestrian stops in a

[32] That is, both the demand and success rate could be used to estimate the number of pedestrian stops occurring in an area (census block group, district, or other area of choice). The constant in the regression equation is small such that we need not be concerned about it. Since there is some error in this process, a margin of error should be defined as well. That is, some degree of departure from the expected value of number of pedestrian stops should be allowed. Later in the study we will discuss some suggestions as to what margin of error might be used.
[33] That is, here, unlike in Table 5a or 5b, we are "forcing" these variables into the equation, even though they are not statistically significant.

census block group.[34] Moreover, the inclusion of these two race variables does not substantially impact the regression coefficients for the three original variables in Table 5b (although the coefficients do vary somewhat from those reported in Table 5b).[35]

We interpret the results of Table 6 to indicate that the deployment of police to neighborhoods -- if such deployment, in part, were to be for the purpose of stopping pedestrians -- to be plausibly a consequence of the types of calls-for-service received in those areas. **To reiterate, the racial composition of the census block groups is not an independent factor in accounting for the number of stops of pedestrians.**

Table 6. "Race" Model: Number of Pedestrian Stopped by Select Calls-For-Service and Racial Characteristics of the Block Group

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 79.0%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.386	1.400		.275	.783		
# Calls for Service Incivilities	.395	.044	.428	8.921	.000	.331	3.025
# Af. Am. drivers in accidents	-.012	.020	-.025	-.607	.545	.457	2.186
# Af. Am. Residents	-.001	.002	-.023	-.575	.566	.467	2.143
# Hit and Run Calls for Service	.169	.084	.082	2.002	.046	.448	2.231
# Violent Offense Calls-For-Service	-.082	.061	-.074	-1.355	.177	.252	3.969
# of Successful Searches (Drugs/Alcohol)	3.839	.234	.594	16.413	.000	.582	1.719

[34] There are no multi-collinearity issues, although one variable – number of calls for service for violent offenses is marginal with a VIF of 3.97.
[35] We also ran a similar model to that in Table 6 by using the variables in Table 5a, plus the two race based measures, with similar results to that described for Table 6.

Gender and Age Predictors of Pedestrian Stops?

So far we have evaluated whether the number of pedestrian stops varies with the racial composition of the block group, but recall that we also are interested in knowing about gender and age in terms of evidence of "arbitrary profiling". In Table 7 below we present results for the same variables as in Table 6 above, but we add gender and age variables (specifically, the number of female residents in a block group and the number of residents between the ages of 18 of 29)[36] for the purpose of seeing whether those demographic representations aid our explanation of pedestrian stops. That is, we are looking to see whether the gender and age composition of a census block group adds to the likelihood that pedestrian stops occur there. Note that we think that it is quite plausible that such factors would be associated with the number of pedestrian stops since it is well known that men participate in a wide variety of criminal activities (with some exceptions, such as shoplifting), as conventionally defined, much more often than women. It is also the case that young people, particularly those over 16 and under 30, participate in crime more often than those of older ages. We find that the regression coefficients are statistically significant for gender and age in Table 7. We interpret this to mean that there is indeed much lower participation in offenses or suspicious behaviors for females and more participation among the young. Note, however, that neither of the measures of an African American presence (residents nor drivers in accidents), are related to the number of pedestrian stops.[37]

[36] We tested for the effects of various age groupings, and the 18 to 29 age grouping was statistically significant.

[37] Although one of the variables, number of violent offense calls-for-service, triggers the multi-collinearity diagnostic with a VIF of 4.0, the coefficients and standard errors are very similar to models in which the VIF is at a lower amount, so we go ahead and include the variable in the model.

Excessive Pedestrian Stops of African Americans?

Although we have presented evidence to suggest that the deployment of officers and the occurrence of stops of pedestrians may be a function of the types of crimes reported by the citizens in their calls-for-service, this does not necessarily indicate that African Americans are not stopped excessively in particular areas of the CMPD jurisdiction. We have only shown above that in general the number of pedestrian stops does not vary with

Table 7. Deployment Model of Number of Pedestrian Stops With Gender and Age Variables Included

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 80.6%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	3.285	1.696		1.936	.054		
# Incivility Offense Calls-for-Service	.388	.043	.420	8.982	.000	.321	3.117
# of African American Drivers in Accidents	-.010	.019	-.021	-.529	.597	.446	2.241
# of African American Residents	-.002	.002	-.030	-.662	.509	.349	2.865
# of Hit and Run Calls for Service	.075	.090	.037	.826	.410	.360	2.779
# of Violent Offense Calls-For-Service	-.066	.059	-.059	-1.113	.267	.247	4.047
# Successful Consent Searches (Drugs/Alcohol)	3.829	.225	.592	17.002	.000	.580	1.725
# Residents Ages 18 to 29	.014	.003	.187	4.743	.000	.451	2.215
# of Female Residents	-.007	.002	-.145	-3.701	.000	.458	2.182

the number of African Americans present – at least not independently of the other variables in the model.[38] In Table 8 we examine specifically the number of African Americans stopped. The table presents a model addressing the question of whether or

[38] Recall that the correlations above indicate that there are statistically significant correlations between the number of African American residents and drivers in accidents with pedestrian stops. The model shows that there is no independent effect of those variables, net of the other variables in the model.

not the number of African Americans stopped is "excessive" in a particular census block group. (There are 278 census block groups in the analysis.) In this model the dependent variable is the number of African Americans stopped. Omitted from the tables are variables from Table 4 that were tested but not found to be statistically significant. With 59.9% of the variance explained, the variables tested and found to be statistically significant are: the number of whites stopped (entered as a control variable for the stop "workload" in a block group), number of calls-for-service for violent offenses, number of incivility calls-for-service, and number of calls-for-service for assaults. As such the results look generally similar to those reported above for all pedestrian stops. Again, the variable measuring calls-for-service for incivility offenses is by far the most important determinant of the stops of African Americans. As observed earlier, the number of violent offenses has a negative independent effect on the number of pedestrian stops of African Americans. We interpret this to reflect the fact that violence is not as concentrated in areas as are incivility type offenses. Also, many violent crimes are committed in domestic situations and among acquaintances or friends. If so, it is understandable that pedestrian behaviors might be inversely related to such calls-for-service.[39] Also, armed robbery of a business, one component of the violent crimes index studied here, probably seldom involves pedestrian suspects (most probably the robber escapes via a vehicle). Furthermore, street robberies of citizens are crimes that are committed at times and in places where there are few witnesses, and thus pedestrian stops may not be a common means to apprehend such perpetrators. Note that we are only trying to account for the fact that the regression coefficient is negative – the correlation

[39] That is, the types of neighborhoods with domestic violence or non-stranger violence may tend not to be the neighborhoods with many pedestrians.

coefficient is positive, .508. Thus, neighborhoods with more violent offenses are more likely to be experiencing stops of pedestrians than neighborhoods with less violent offenses being called in via 911 calls. Net of the other variables in the model, however, the effect of the number of violent crime calls for service is negative.

We are interested in knowing what other factors might be associated with the stopping of African American pedestrians. We hypothesized that in areas where there is a specific problem with street trafficking in drugs that there might be more stopping of African American pedestrians (whether for legitimate reasons, such as suspicious behavior associated with carrying drugs, or for illegitimate reasons, such as targeting African Americans).

Table 8. Regression Analysis of Number of African Americans Stopped as Pedestrians in Census Block Groups

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2=59.9%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-7.170	2.539		-2.824	.005		
# White Pedestrians Stopped	.419	.155	.117	2.696	.007	.772	1.295
# Violent Offense CFS	-.192	.062	-.185	-3.096	.002	.406	2.463
# Incivility CFS	.679	.052	.785	13.175	.000	.409	2.443
# Assaults	3.130	.960	.146	3.262	.001	.728	1.374

In Table 9 below we show the results of an analysis aimed at determining whether the success in consent searches is a factor in explaining the number of African American pedestrian stops (as it was found to be in the models for number of pedestrian stops for people of all races). It is likely that the targeting of potential drug offenders is a likely explanation for the relatively high number of African American stops of pedestrians. The "war on drugs" has been cited widely as a source for racial profiling. It would be useful to document the extent to which the success rate in consent searches accounts for the number of African American pedestrian stops. We are not proposing that if there are more African Americans stopped where consent searches have been successful that is evidence of racial bias. Rather we are only trying to account here for why there are relatively many African Americans stopped in some areas. It may be that the police had acceptable reasons for stopping individual African American pedestrians. To reiterate, we are trying to determine if the success rate of consent searches (where "success" is usually defined as drug contraband) in a neighborhood is in part an explanation for the number of African Americans stopped.

We also included among the independent variables in our model the number of African American residents and drivers in accidents, as well as the number of females and the number of individuals between the ages of 22 and 29, so as to determine if the number of African Americans stopped as pedestrians varied with these characteristics.[40] We assume that there will simply be more stops of African Americans in neighborhoods where African Americans are present.

Table 9 shows the results of the analysis. As we hypothesized, the areas with more successful consent searches were the areas with more stops of African American pedestrians (Standardized B=.605). Note that the explained variance is similar to that found in the models above of number of pedestrian searches and higher than the 60% in the model of Table 8, with 80.4% of the variance explained here. These results indicate to us – perhaps what is obvious to many -- that successful "hit rate" for drugs is an

[40] We also tested a variable number of residents between the ages of 18 and 22, but found it statistically insignificant, and omitted it from the model represented in the table.

important component in the explanation of pedestrian stops of African Americans. In the model the inclusion of the drug measure competes with the number of calls for service for assaults, reducing the latter's effects to statistical insignificance. The number of "break and enter" calls has a small negative effect on the number of African Americans stopped as pedestrians. The number of females is unrelated to the number of African American pedestrians stopped, nor is the number of residents between the ages of 22 and 29.

Also in Table 9, we see that the racial composition of the area as measured by census population counts is not a predictor of the number of pedestrian stops of African

Table 9. Number of African American Pedestrian Stopped By Characteristics of Block Groups, Including Number of Successful Consent Searches

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 80.5%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	.462	1.596		.289	.773		
# Whites Stopped as Pedestrians	.197	.133	.055	1.479	.140	.510	1.962
# of Successful Consent Searches (Drugs & Alcohol)	3.667	.215	.605	17.044	.000	.560	1.786
# Incivility Calls for Service	.352	.036	.407	9.676	.000	.399	2.504
# of Calls for Service for Break and Enter	-.110	.053	-.093	-2.100	.037	.361	2.768
# Af. Am. Residents	.000	.002	.005	.126	.900	.417	2.399
# Af. American Drivers in Accidents	.002	.015	.006	.169	.866	.619	1.616
# Residents Aged 22-29	-.005	.004	-.069	-1.452	.148	.313	3.196
# Female Residents	-.0000584	.002	-.001	-.028	.978	.368	2.714

Americans, nor is the number of African American drivers in accidents predictive of such stops, net of the effects of the other variables in the model. We interpret this finding to mean that African American pedestrian stops are largely determined by demand and success and not the racial composition of the areas per se.

The important implication of Table 9, however, is that success in finding contraband (drugs and alcohol) is the strongest predictor of the number of African Americans being stopped across block groups (St. Beta = .605). This evidence is useful for interpreting any disparity in specific block group areas with regards to race, a topic that we discuss in the next section of the report.

Flagging Census Blocks with Relatively High Counts of African American Pedestrian Stops

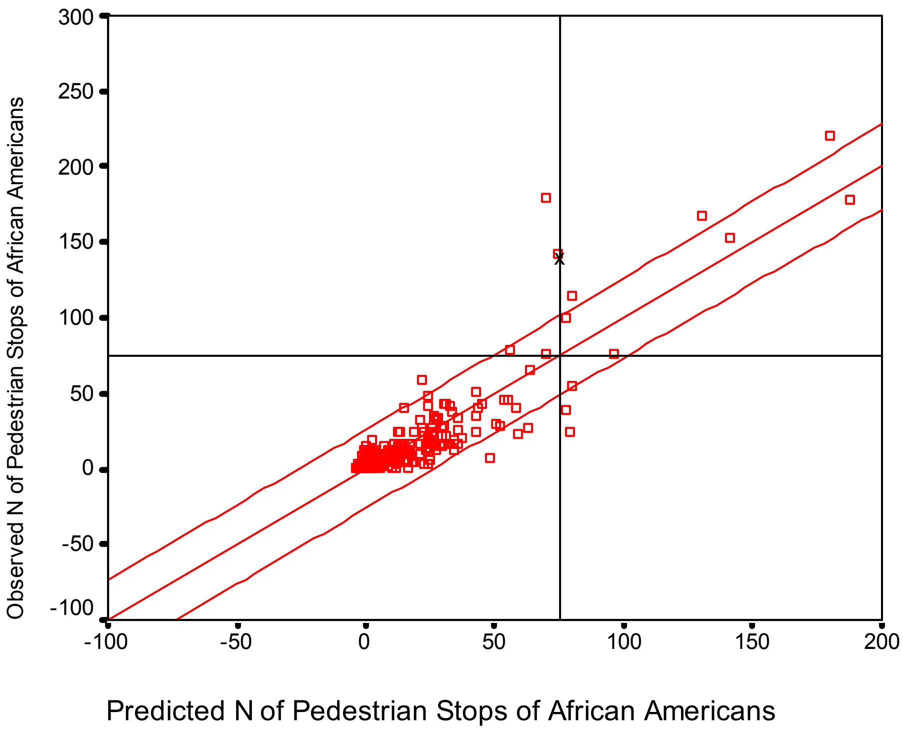
Census block groups with relatively high numbers of African American pedestrian stops can be identified using the predicted values from the equations -- such as those represented in Tables 8 and 9 -- as a referent against which to determine how high (or low) the number of African American pedestrian stops is in a particular census block group area. Note that as researchers we can only provide rather limited information as to the extent and nature of the stops of African American pedestrians in the block groups studied here. Whether or not that number is excessive depends in part on how much policing is valued or deemed appropriate, given varying levels of different community problems. Our purpose here is to provide a means for identifying areas with a suspiciously high number of African Americans stopped as pedestrians. Knowing what areas have high rates and the extent to which the numbers are disparate from a reasonable estimate of how many stops there should be, can be useful for decision makers. That is, our models can be used by the CMPD decision makers (including the civilian advisory board to this project) to determine whether those rates might be excessive. That is not a determination that we can make as researchers with the data that we have available to us.

The model in Table 9 can be reduced or trimmed with little loss of predictive efficiency. Two variables – the number of successful consent searches and the number of incivility calls for service – account for 79.5% of the variance in the number of African Americans stopped (compared to 80.4% using the full model in Table 9). The results are thus very similar to that found in the models above for the number of pedestrian stops irrespective of race. Here, using only the two predictor variables, we find that one successful pedestrian consent search results in 3.7 pedestrian stops of African Americans and each call for service for incivility offenses results in .33 pedestrian stops of African Americans (results not shown in a table).

We take the trimmed model and use it to generate estimates of which census block areas are positive and which are negative outliers. The results are shown in Figure 1. Along the X or horizontal axis is the number of African Americans predicted to be stopped as pedestrians, given the volume of calls for service for incivility offenses and the number of successful consent searches (in which drugs or alcohol were found). Along the Y or vertical axis is the number of African Americans actually stopped as pedestrians in 2002. Each small (red) square in the figure corresponds to a census block group. Most census block groups have small numbers of African Americans stopped as pedestrians and thus are clustered in the lower left quadrant of the figure.

There are three "diagonal lines" from the lower left to upper right in the figure. The middle of these lines represents the regression line: the exact predicted value of the number of African Americans stopped in each census block group. The outer two lines represent the 95% confidence intervals of the regression line. That is, if repeated samples were drawn, we would expect that there would be some variation in the predictions of the equation, but that in 95% of the samples the slopes would fall within this confidence interval. We define here -- somewhat arbitrarily -- an outlier as a census block group that lies outside of the 95% confidence interval.[41] As can be seen in the graph, there are six

Figure 1. Predicted Number of African Americans Stopped as Pedestrians by Observed Number of African Americans Stopped



census block groups lying above the upper confidence interval, and about five lying below the lower confidence interval. We refer to the former as "positive outliers" and the latter as "negative outliers". Below we discuss some reasons why these districts may be

[41] Other definitions of outliers are possible, such as any observation lying a certain proportion away from (distant from) the predicted values, or an absolute number above or below the regression line.

outliers. Also note in the figure two perpendicular "reference lines" – each corresponds to the value of 75, a value arbitrarily chosen to show that when the regression line predicts that 75 African American pedestrians should be stopped we have no census block group with exactly 75 African Americans stopped as pedestrians. However, we do have a positive outlier with approximately 140 African American pedestrians stopped. This outlier is marked with an "x". The question we must address is why does this census block group (like the other positive outlier in the figure) have so many African American pedestrian stopped -- 65 more than the 75 predicted by the model?

Evaluating Outliers: Number of African American Pedestrians Stopped

The models discussed above are likely to not capture all of the specific factors that may account for the positive and negative outliers identified in Figure 1. Three such factors that we as researchers thought might be relevant in accounting for the positive outliers include: 1) mobility of the street drug market; 2) organized citizen demand for police services: and 3) a history of drug trafficking before 2002. That is, as police make arrests of pedestrians for possession of contraband, the drug sales in an area may move to other locations. Thus, suspicious pedestrians in the original neighborhood become less likely to have drugs on them, thereby driving down the number of successful drug "hits" when pedestrian consent searches are conducted. The second reason that we speculated for high numbers of African American pedestrians being stopped in an area, relative to the model's prediction, may be that the degree of citizen organization in an area may be high and demanding of a more active police presence.[42] Citizen groups or the leadership

[42] Since all of the positive outliers in Figure 1 have a vast majority of residents who are African American, it is likely that most of the pedestrians in those areas are also African American.

of institutions (churches, schools, public housing complexes, etc.) may bring about a greater police presence in a neighborhood as "demand" is registered in venues supplemental to 911 calls (demand expressed at community meetings, or phone calls to the police that are not made using 911). Third, we thought it plausible that a neighborhood with a history of drug sales would continue to be monitored and subject to pedestrian stops and searches. The police are, in large part, a reactive organization. The drug market may shift from one neighborhood to another over time, such that a specific neighborhood may experience a dip in drug activity in the short run, but in the long run drug sales will come back. The primary means that the police have to know if the drug market is "back" is in the contraband "hit rate" of stops resulting in searches. In any event, the demand for services in a short period of time (say a few months) would not be a good reason to terminate vigilance in looking for evidence of drug transactions.

Our thoughts were generally similar for the negative outliers. For one, if the drug market has moved into a new area, the police may "lag" in their response to that movement such that they fail to look as intensely in the new drug-sale area as they might, given the extent of the problem. Presumably over time the police will realize that a shift in the market has occurred and increase scrutiny in the new area. In the meantime, that area will be a "negative outlier" – having too few African Americans stopped.[43] Areas with a relative lack of stops of African Americans may also be areas where there is no institutional presence or organizational basis for making demands and where the police perceive that the drug action has moved elsewhere (yet calls for service and search "hit rates" may be high).

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[43] Again it is the case that the specific areas here are mostly African American in composition.

In addition to the reasons cited above for positive or negative outliers, we found that there were additional reasons suggested by some of the leadership of the police officers working in the areas with the positive and negative outliers. Maps of the outlier areas were presented in a meeting in December, 2003. The leadership present was familiar with the areas and suggested that some of the following factors may account for the positive outliers: 1) presence of a local college (historically African American) – which may account for more African American pedestrians than in other areas, all else being equal; 2) presence of a public housing complex with a history of drug-related problems; 3) an area is defined by the police as a "hot spot" and has been subject to an "aggressive" police presence (including bike patrols) to address the problems in that area; 4) presence of convenience stores (where alcohol is sold) and where "winos" hang out – the latter often the subject to pedestrian stops; 5) "red light" area with street prostitution a problem that the police were focusing on; 6) presence of a large "homeless" population near the city shelter and soup kitchen (presumably there is a greater police presence and pedestrian searches are incidental to that presence; also some of the behaviors of the homeless are triggering police stops of the homeless); 7) area is a central downtown area (where there are many pedestrians due to the concentration of people in relatively small areas); and 8) area is near where there are many "special events" (e.g., stadium events) which bring many of people into the area (thus, our model would not be able to account for the volume of pedestrians, including both African Americans and whites).

As for "negative outliers" the police leadership suggested some of the following factors: 1) area is subject to a federal drug enforcement effort so local police have less of a role; 2) area is largely Hispanic (thus, there would be fewer African Americans stopped);[44] 3) area is where there has been "Neighborhood Action Teams" involved to reduce crime – this type of police presence is less oriented to stop and search interventions; 4) area includes a research park (where presumably there is little activity at night, low crime, and (possibly) relatively few African Americans – driving down the total numbers of African Americans for the whole census block group); 5) area is "hard to get to" in that there is no "thoroughfare" running through the area (thus, police presence would be less than otherwise would be the case); and 6) some officers are under-reporting their stops (not filling out the stop forms). In the course of the discussion it was mentioned that a couple of the negative outliers did not seem to have any obvious explanations other than they were next to an area that was a positive outlier, suggesting a "lightning rod" effect where one neighborhood drew the police attention while the other did not (despite having a high volume of calls for service for incivility offenses).

As researchers, we thought that the comments of the police leadership about the specific positive and negative outliers to be quite informative. The reasons mentioned are plausible reasons why the variable measuring "number of African Americans stopped" has a relatively high or low value in a particular census block area. While such informational input does not constitute systematic evidence, they do represent plausible explanations for the high or low counts in these census block areas. We leave the interpretation of the value of these explanations to the citizen advisory committee and CMPD leadership, who will have to make a decision as to the value of the suggested explanations.

[44] Note that there are "pockets" of Hispanics in Charlotte, but relatively few within most of the census block areas. The variable "number of Hispanics" was tested and not found to be a statistically significant predictor of number of pedestrian stops nor of number of African American pedestrian stops.

Vehicular Stops

Thus far we have evaluated the question of whether deployment is a possible explanation for racial disparity in the number of pedestrian stops. The other, more common type of stop of a citizen is a vehicular stop. Stops of vehicles, we expect, could show a different pattern of findings than that of pedestrian stops. One possible reason for the difference is that vehicle stops most often are a result of some violation involving the vehicle (e.g., speeding) whereas pedestrians are presumably stopped because of suspicious citizen behaviors. Also, in vehicular stops the race of the driver is often unknown at the time the stop is initiated. Because vehicular stops obviously occur on the streets and highways of the CMPD jurisdiction, we hypothesize that the number of African Americans stopped should be more strongly related to the number of African Americans in accidents than was the case with pedestrian stops. Also, it should be noted that vehicular stops very seldom involve -- relative to pedestrian stops -- a motivation to search or suspicion of drugs. This is largely true because most vehicular stops are for vehicle violations having nothing to do with drugs.

Table 10 shows the proportion of stops by type of reason for the stop. (The table is presented for 77,125 geocoded stops and is very similar to a table for all 94,630 stops for 2002.)[45] By far, speeding is the most common behavior mentioned as the reason for the vehicular stop (41.9% of the stops are for speeding). The second most common type of reason for a stop has to do with registration problems (expired tags, expired inspection stickers, and other problems such as expired license -- presumably expired licenses are

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[45] Note that the percent African American in the full vehicular stop data is 41.3% while in the geocoded subsample it is 42.3%. Thus, the geocoded subsample, representing 81.5% of all the stops, contains an overrepresentation of African Americans.

rarely the reason for a stop since the police seldom know prior to a stop that someone has an expired drivers license).

Most of the time a vehicular stop results in a citation. Table 11 shows the outcomes of the stops. The second most common outcome is a verbal warning. The vast majority of vehicular stops are initiated by the officer – 97.2% (not reported here in

Table 10. Vehicular Stops by Reason for Stop

	Frequency	Percent	Valid Percent	Cumulative Percent
Driving while intoxicated	992	1.3	1.3	1.3
Investigation	3324	4.3	4.3	5.6
Other	6379	8.3	8.3	13.9
Unsafe Driving	4208	5.5	5.5	19.3
Speeding	32297	41.9	41.9	61.2
Seat Belt	4399	5.7	5.7	66.9
Stop Light/Sign	4768	6.2	6.2	73.1
Vehicle Equipment	4765	6.2	6.2	79.3
Vehicle Regis-tration, tags, etc.	15993	20.7	20.7	100.0
Total	77125	100.0	100.0	

Table 11. Outcome of Vehicular Stops

	Frequency	Percent	Valid Percent	Cumulative Percent
Arrest	3814	4.9	4.9	4.9
Citation	51282	66.5	66.5	71.4
None	3098	4.0	4.0	75.5
Verbal Warning	12727	16.5	16.5	92.0
Written Warning	6204	8.0	8.0	100.0
Total	77125	100.0	100.0	

Table 12. Examples of Comments Written by Patrol Officers Making Vehicle Stops

Saw driver put seatbelt on as I made...
56 mph in 35 mph zone
school zone violation
44 mph in 25 mph school zone
SAME ARRESTED FOR VIOLATING HIS LIMITED
The driver was DWLR
Subject was stopped for no insurance and
54 in a 35
the vehicle had no tag displayed, but after...
DWI and REVOKED LICENSE DUE TO RESTRICTI
expired tag
51 in a 35
SEIZED REVOKED LICENSE FROM OPERATOR.
R-62 in a 35
Vehicle was stopped after I ran the tag
62 in a 35 and driver was DWLR
SCHOOL ZONE
Speeding in school zone 45 in 25
Red light violation.
51/35
School zone violation
Subject was sitting in parking lot of…
51 in a 35
Tag showed expired by 13 days and subject
School Zone violation- Subject just move
STOP FOR SPEEDING CIT FOR SEAT BELT
Speeding 43 in 25 school zone
44 in 25 school zone
Subject was stopped after making a right
cooperative
school zone violation and expired tag
No tag, Passing in no pass zone
56 in a 35 zone
54 in a 35
No tag displayed and after running vin
Stopped for possible 10-55. she was found
50 in school zone
One of the worst run stop signs I have seen
school zone violation
ARRESTED FOR WARRANTS
school zone violation.
Tag was run...NCIC showed no operator's
The driver was nol and driving with no l d
drive after consume <21.
searched car, nothing located. prostitute
insurance stop also
Expired tag 2-15-02
53 in a 35
Subject did not have lights on at dark.

table). The remainder of the calls are citizen initiated or initiated by another officer or a report from a law enforcement source. The routine nature of most police stops is reflected in the comments officers write on the stop form. Some randomly selected comments are presented in Table 12. For example, some drivers were “DWLR” or “driving with license revoked.” Many are speeding with the observed speed given, followed by the posted speed limit. Obviously, most stops are for ordinary vehicular offenses.

Table 13 Age of Driver Stopped

Age	Frequency	Percent	Valid Percent	Cumulative Percent
Less than 15	15	.0	.0	.0
15 to 20	9,494	12.3	12.3	12.3
21 to 30	29,817	38.7	38.7	51.0
31 to 50	31,715	41.1	41.1	92.1
51 to 64	4,926	6.4	6.4	98.5
65 or more	1,158	1.5	1.5	100.0
Total	77,125	100.0	100.0	

As for the demographic characteristics of those stopped, most are young with those between the ages of 21 and 30 representing the most frequent category of driver in a vehicle stop – 38.7% (Table 13). Only 1.5 percent of those stopped are over 65 years.

In Table 14 we see that the percent of drivers stopped who are African American is 42.3%, while whites make up 51.3% of all those in vehicular stops. The proportion of those stopped who are male is about two thirds. A slightly smaller proportion is observed for African American males (62.9%) as compared to all males (64.9%).

In Table 15 we examine the relationship between the type of vehicle driven and the race/ethnicity of the driver. We see, for instance, that African American drivers stopped are more likely to be stopped driving a car than are whites (85.5% versus 72.4%). Whites, on the other hand, are more likely to be stopped driving a SUV than are African Americans (12.1% versus 7.4%). Hispanics are even less likely to be driving an SUV, and are similar to whites in the use of pick-up trucks in the stop context (10.5% and 9.8% for Hispanics and non-Hispanic whites, respectively). We show these patterns in part to demonstrate that there seem to be racial/ethnic differences in the type of vehicles driven,

Table 14. Race by Gender (Drivers Stopped)

		GENDER		Total
		F	M	
Asian	Count	435	853	1288
	% within RACE	33.8%	66.2%	100.0%
	% within GENDER	1.6%	1.7%	1.7%
African American	Count	12108	20531	32639
	% within RACE	37.1%	62.9%	100.0%
	% within GENDER	44.8%	41.0%	42.3%
Indian	Count	36	51	87
	% within RACE	41.4%	58.6%	100.0%
	% within GENDER	.1%	.1%	.1%
Unk	Count	617	2897	3514
	% within RACE	17.6%	82.4%	100.0%
	% within GENDER	2.3%	5.8%	4.6%
White	Count	13849	25748	39597
	% within RACE	35.0%	65.0%	100.0%
	% within GENDER	51.2%	51.4%	51.3%
Total	Count	27045	50080	77125
	% within RACE	35.1%	64.9%	100.0%
	% within GENDER	100.0%	100.0%	100.0%

yet the predominant vehicle type involved in a stop across categories of race/ethnicity is the car. Also, these results suggest that if the type of vehicle was being used by police as a proxy for race, that there would be many errors to the "targeting" of African American drivers.[46]

In Table 16 we see that the percent of those stopped who are African American varies across the reasons for the stop. For example, African Americans are much more likely to be found among those who are stopped for investigative reasons (56.9% of those stopped for investigative reasons are African American) than are whites (24.8%). African

Table 15. Type of Vehicle Stopped by Driver's Race/Ethnicity

Vehicle Type	Basis for Percentage	Race/Ethnicity						Total
		Asian	Af. Am.	Hispanic	Indian	Unk.	White	
Car	Count	1300	33213	7658	61	1425	30619	74276
	% within Vehicle	1.8%	44.7%	10.3%	.1%	1.9%	41.2%	100.0%
	% within Race	81.9%	85.3%	76.9%	77.2%	81.8%	72.4%	78.5%
Motorcycle	Count	5	95	12	0	3	137	252
	% within Vehicle	2.0%	37.7%	4.8%	.0%	1.2%	54.4%	100.0%
	% within Race	.3%	.2%	.1%	.0%	.2%	.3%	.3%
Other	Count	73	1432	662	5	117	2252	4541
	% within Vehicle	1.6%	31.5%	14.6%	.1%	2.6%	49.6%	100.0%
	% within Race	4.6%	3.7%	6.6%	6.3%	6.7%	5.3%	4.8%
PickUp	Count	66	1346	1049	6	72	4151	6690
	% within Vehicle	1.0%	20.1%	15.7%	.1%	1.1%	62.0%	100.0%
	% within Race	4.2%	3.5%	10.5%	7.6%	4.1%	9.8%	7.1%
SUV	Count	144	2873	581	7	125	5137	8867
	% within Vehicle	1.6%	32.4%	6.6%	.1%	1.4%	57.9%	100.0%
	% within Race	9.1%	7.4%	5.8%	8.9%	7.2%	12.1%	9.4%
Total	Count	1588	38959	9962	79	1742	42296	94626
	% within Vehicle	1.7%	41.2%	10.5%	.1%	1.8%	44.7%	100.0%
	% within Race	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

[46] Thus, for example, cars could be targeted for stops because cars -- rather than other vehicle types -- are more often found to have an African American driver than any other race of driver. Yet, in approximately 55% of the stops the driver would not be African American, as can be seen in Table15.

Table 16. Race of Driver in Stop By Reason for Stop

Reason for Stop		Race/Ethnicity						Total
		Asian	Af. Am.	Hispanic	Am. Ind.	Unk.	White	
DWI	Count	19	279	335	3	20	593	1249
	% within Reason	1.5%	22.3%	26.8%	.2%	1.6%	47.5%	100.0%
	% within Race	1.2%	.7%	3.4%	3.8%	1.1%	1.4%	1.3%
Investigative	Count	41	2216	624	1	46	967	3895
	% within Reason	1.1%	56.9%	16.0%	.0%	1.2%	24.8%	100.0%
	% within Race	2.6%	5.7%	6.3%	1.3%	2.6%	2.3%	4.1%
Other	Count	89	3314	1069	8	133	2856	7469
	% within Reason	1.2%	44.4%	14.3%	.1%	1.8%	38.2%	100.0%
	% within Race	5.6%	8.5%	10.7%	10.1%	7.6%	6.8%	7.9%
Unsafe Driving	Count	110	2054	699	7	95	2199	5164
	% with Reason	2.1%	39.8%	13.5%	.1%	1.8%	42.6%	100.0%
	% within Race	6.9%	5.3%	7.0%	8.9%	5.5%	5.2%	5.5%
Speeding	Count	843	13849	3075	34	889	22521	41211
	% within Reason	2.0%	33.6%	7.5%	.1%	2.2%	54.6%	100.0%
	% within Race	53.1%	35.5%	30.9%	43.0%	51.0%	53.2%	43.6%
Seat Belt	Count	91	2194	516	2	97	2547	5447
	% within Reason	1.7%	40.3%	9.5%	.0%	1.8%	46.8%	100.0%
	% within Race	5.7%	5.6%	5.2%	2.5%	5.6%	6.0%	5.8%
Stop Light/Sign	Count	130	1932	691	6	140	2685	5584
	% within Reason	2.3%	34.6%	12.4%	.1%	2.5%	48.1%	100.0%
	% within Race	8.2%	5.0%	6.9%	7.6%	8.0%	6.3%	5.9%
Vehicle Equipment	Count	89	2859	983	4	106	1463	5504
	% within Reason	1.6%	51.9%	17.9%	.1%	1.9%	26.6%	100.0%
	% within Race	5.6%	7.3%	9.9%	5.1%	6.1%	3.5%	5.8%
Vehicle Registration	Count	176	10262	1970	14	216	6465	19103
	% within Reason	.9%	53.7%	10.3%	.1%	1.1%	33.8%	100.0%
	% within Race	11.1%	26.3%	19.8%	17.7%	12.4%	15.3%	20.2%
Total	Count	1588	38959	9962	79	1742	42296	94626
	% within Reason	1.7%	41.2%	10.5%	.1%	1.8%	44.7%	100.0%
	% within Race	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Americans are also more likely to be represented among the ranks of those stopped for vehicle equipment problems or for vehicle registration problems (including insurance violations and lack of driver's license). The finding on investigative stops is suggestive of possible racial profiling, as African Americans are being stopped at a higher rate for suspicion than are whites. Alternatively, African Americans may simply be in contexts that are more suspicious, resulting in investigative stops. The finding on vehicle equipment and registration perhaps suggests a behavioral difference along social class lines. That is, those with less economic means are more likely to have vehicles with equipment and registration-type problems (being less able to afford -- or simply delaying -- repair or filing of appropriate papers).

Before modeling the number of vehicular stops by geographic area, using the census block group as the unit of analysis -- as we did for the pedestrian stops earlier in the report -- we report in Table 17 on the correlation matrix among variables hypothesized to be predictors of the number of vehicular stops. (Correlations reported in this table that are greater than +/- .10 are statistically significant at .05 level.) As such, the correlation matrix reported in Table 17 looks much like the one reported earlier in Table 4. The variables in the left-hand column, with the exception of the first variable (number of vehicular stops in a block group), are the same.[47]

We see that the number of accidents in block groups correlates .63 with the number of vehicular stops.[48] This relatively high correlation validates our use of accidents as an indicator of the presence and activity level of drivers across the

[47] In an earlier draft the 13th variable was number of owner occupied, whereas here it is the success rate of searches resulting from a consent search in the vehicular context. The number of owner occupied dwellings was not found to be statistically significant in any of the equations.
[48] By comparison, for pedestrian stops the correlation with number of accidents was .53 (Table 4).

geographic areas of the city. We interpret this coefficient to mean that the volume of drivers subject to stops is being measured reasonably well by the number of accidents in the areas. At the same time, specific types of vehicular calls for service in an area are lowly correlated with the number of vehicular stops (specifically, number of disabled vehicle calls, .08, and number of hit and run calls, .14).

The majority of vehicular stops are initiated by patrol officers while they go about their various duties. Where those duties take them is in part a function of the calls for service for non-vehicular responses (such as for violent crime, incivility calls, and breaking and entering). As we can see there are moderately high correlations with these calls for service and the number of vehicular stops in each district (.45, .46 and .52, respectively, in the table). That there are slightly higher correlations between the number of African American drivers in accidents and vehicular stops (.63) as well as between number of white drivers in accidents and vehicular stops (.53), reflects the fact that the vast majority of the driving population is made up of African Americans and whites. That is, if the number of drivers in accidents is highly correlated with number of vehicular stops (.63), we would expect that the two relatively large subpopulations (African Americans and whites), would each have similarly high correlations. To a lesser extent the resident population correlates with the number of vehicular stops: number of residents (.26), number of African American residents (.36) and number of white residents (.02). These latter numbers cast doubt on the validity of exclusively using residency demographic characteristics to account for variation in stop behavior. Interestingly, the number of African American residents correlated more highly than does the number of white residents (where, in fact, the correlation is not statistically significant

Table 17. Correlations With Number of Drivers Stopped

	2.	3.	4.	5.	6.	7.	8.	9.	10.	11.	12.	13.
1.# Vehicular Stops	.63	.45	.46	.52	.26	.08	.14	.36	.63	.02	.53	.52
2. # Drivers in Accidents		.38	.41	.41	.23	.17	.15	.24	.92	.08	.95	.41
3. # Violent Offense Calls			.77	.80	.20	-.16	.00	.72	.56	-.28	.17	.61
4. # Incivility Calls				.59	.01	-.12	.02	.48	.56	-.32	.25	.61
5. # Break and Entry Calls					.42	-.15	-.00	.73	.54	-.04	.23	.53
6. # Residents						-.10	.03	.42	.15	.82	.23	.06
7. # Disabled Vehicle Calls							.62	-.19	.11	.01	.21	-.07
8. # Hit and Run Calls								-.05	.12	.05	.14	.02
9. # Af. American Residents									.42	-.16	.06	.53
10. # Af. American Drivers in Accidents										-.12	.75	.52
11. # White Residents											.21	-.27
12. # White Drivers in Accidents												.27
13. # Successful Searches												

-- meaning we cannot reject the null hypothesis that the correlation is zero). We interpret the .36 correlation to mean that there is more policing in the form of vehicular stops occurring in African American neighborhoods. (However, as we will show below, the level of policing does not seem to be a function of the number of African American citizens when population size is controlled for statistically in a regression equation.) Some of the other correlations of note in the table include the very high correlations between the number of accidents and the number of whites in accidents (.95) and number of African Americans in accidents (.92). These high levels of inter-correlations among independent variables prohibit us testing each of these variable's effects independently other two. It should also be pointed out that the number of African Americans correlates only modestly with the number of African American residents (.42), as does the number of whites in accidents and in residency (.21). Again, these results call into question the use of residency demographics to explain exclusively vehicular stops. We will not try to interpret all of the correlations in Table 17, but rather leave the reader to do so.

We now turn to address the question of whether the deployment of CMPD police officers is primarily attributable to the traffic and demographic characteristics of the drivers in the block groups (as measured by accidents), or to other characteristics. In Table 18a we see the regression model of the number of vehicles stopped with the statistically significant variables from Table 17 that survived the test.[49] Only four variables were found to be statistically significant: number of vehicular accidents, number of residents ages 18 to 29 as per the 2000 census), number of incivilities reported by citizens in calls for service, and number of break and entry calls for service reported

[49] Again, as with pedestrian stops, we omit the variable successful search rate (here defined as successful consent searches in which drugs or alcohol are found in the vehicular context).

by citizens. None of the other demographic-related variables (number of whites, number of African Americans – drivers or residents) were found to have an independent effect in the models tested.[50]

Thus, we can conclude that the deployment of CMPD officers with the resulting consequence of vehicular stops is largely a function of the volume of accidents, size of population and the demand for police services as indicated by incivility and "break and entry" calls for service. Race-specific demographic variables were not found to be statistically significant. Due to high collinearity, we cannot test simultaneously the effect of the number of African Americans in accidents and the total number of drivers in accidents. Nevertheless, we think it is unlikely that the race of the drivers in accidents dictates how many vehicle stops occur in a block group because of the CMPD use of MPP (Managing Patrol Performance) software in making deployment decisions. That is, the deployment process in CMPD is a very "rational" and monitored process involving many variables, such as: call-for-service rate, priority, time to arrival, travel times, etc. We argue that it is more reasonable to assume that the volume of accidents is a better measure of what influences deployment decisions than is the number of African American drivers in accidents (recall that the two measures are correlated .92).[51]

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[50] Specifically, we followed a forward entry procedure in which the variable with the largest partial correlation was entered until there were no statistically significant variables left to enter. Note that due to multi-collinearity, the number of African American drivers and African American resident population could not be tested in the same equation. Also, number of accidents and number of accidents involving African American drivers could not be tested in the same equation due to multi-collinearity. In the latter case we left in the number of drivers in accidents rather than the number of African American drivers. Clearly here the data do not permit a definitive independent effect of how the race of the drivers in accidents affects the "deployment" of officers. However, we can assess the effect of the race of the residents, and there are no statistically significant effects to report.

[51] Stated another way, it seems more reasonable to assume that the number of accidents is a good proxy measure for all of the many variables that go into determining how many officers are deployed to each district (by time of day) than it would be to assume that the number of African American drivers is determining deployment. Note that this is an assumption and the high inter-correlation of these two variables prohibits empirical test of it. In a model without number of accidents but including number of

We next attempted to address the question of whether the gender composition of the block groups had an effect. The variable "number of women drivers in accidents" was too highly correlated, however, with number of accidents, and had to be dropped from consideration for that reason. However, we were able to test the effect of number of women residents and found that it was not statistically significant when included with the independent variables listed in Table 18a.

It should be noted that the R^2 in the model of Table 18a is considerably lower than that reported earlier for pedestrian stops: here it is 48.5%. This indicates that we are explaining about half of the variance about the mean in the number of vehicular stops across block groups, and that there are probably more factors relevant to explaining this variation than we are capturing in the model's list of tested independent variables (essentially the variables in Table 17 plus the gender and age variables discussed in the previous paragraph).

Table 18a. "Deployment" Model of Number of Drivers Stopped By Statistically Significant Characteristics of Block Groups

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 48.5%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	20.657	13.931		1.483	.139		
# of Drivers in Accidents	.557	.058	.416	9.623	.000	.757	1.322
# of Residents 18 to 30 Years Old	.105	.026	.179	4.117	.000	.751	1.332
# of Incivility Calls for Service	.895	.356	.122	2.515	.012	.600	1.667
# of Break and Enter Calls for Service	1.983	.494	.209	4.012	.000	.522	1.917

African American drivers in accidents, the R^2 is lower than in the model using number of accidents (46.9% vs. 48.5%), making the decision to use number of accidents in part an empirical decision (based on the goal of maximizing prediction).

We next look at the effect that successful searches has on the number of vehicular stops in an area. In Table 18b we include the number of successful consent searches (in which drugs or alcohol were found) as a predictor variable. The variance explained is somewhat higher at 51.4% than the 48.5% we found when search success is not controlled for in the model. The variable measuring the number of incivility calls for service becomes statistically insignificant. Success, as measured by the number of successful consent searches (in the vehicular context as opposed to the pedestrian context), is the second best predictor in the model with a standardized beta value of .232. Thus, the model suggests to us that to some extent the number of drivers stopped in a census block group is attributable to the number of successful searches, but primarily it is due to accidents and crimes -- as well as to the age demographics -- of the area.

Table 18b. "Deployment" Plus "Search Success" Model: Number of Drivers Stopped By Statistically Significant Characteristics of Block Groups

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 51.4%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	21.258	13.526		1.572	.117		
# of Drivers in Accidents	.508	.057	.380	8.914	.000	.733	1.364
# of Residents 18 to 30 Years Old	.111	.025	.188	4.470	.000	.749	1.335
# of Incivility Calls for Service	.199	.375	.027	.530	.596	.510	1.961
# of Break and Enter Calls for Service	1.446	.493	.152	2.934	.004	.495	2.021
# of Successful Consent Searches in Vehicular Context (Drugs/Alcohol)	20.304	4.239	.232	4.790	.000	.567	1.762

Flagging Census Blocks with Relatively High Counts of African American Vehicular Stops

The fact that stops of vehicles across census block groups does not vary as a function of the racial composition of those census block groups, net the effects of the other variables tested in the models above, does not necessarily mean that there are block groups without excessively high stops of African American driven vehicles. To identify such block groups we conduct further analysis in which the number of African Americans stopped in vehicles is the dependent variable. We tested all of the variables discussed above, including the gender and age variables, and report those that were statistically significant in Table 19 below. We again encountered problems with multi-collinearity and had to drop the following variables from the analysis: number of white residents, number of accidents and number of white drivers in accidents (the latter two were dropped rather than drop the variable number of African Americans in accidents).

As we can see in the table, the model is able to explain 82.5% of the variance (adjusted R^2), an indication that we are predicting African American stops quite well. Almost all of the variables found to be statistically significant are demographically related: number of African Americans in residency, number of African American drivers in accidents, number of white drivers stopped in vehicular context, and the population count (which has a negative coefficient). The number of incivility calls for service and the number of successful consent searches in vehicular context (in which drugs or alcohol were found) were also found to be significant.[52] Thus, of all the calls for service variables, only the number of incivility calls for service (by citizens) survived the tests.

[52] We omit presenting a model that did not include number of successful consent searches in the vehicular context as the results are quite similar to those presented in Table 19. The explained variance is only lower by 2%, i.e., 80.5% instead of 82.5% found in Table 19. Thus, successful consent searches in the vehicular context does adds only marginally to the predictive ability of the model.

All the other call-for-service variables were statistically insignificant. The model, therefore, indicates that the presence of African American drivers (as measured by African American residency and accidents) is primarily responsible for where there are more stops of African American drivers (with standardized beta coefficients of .347 and .275, respectively.) Success in consent searches plays a role, but a more marginal one, as compared to pedestrian stops.

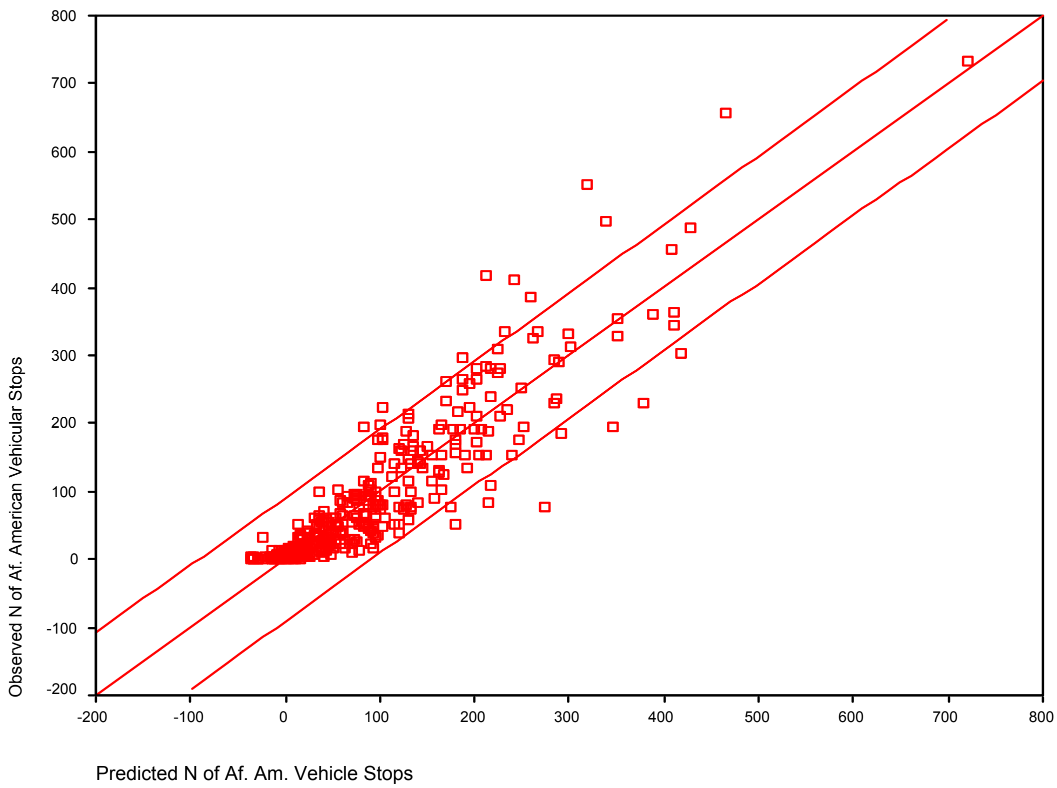
In general we interpret these results to indicate that where we expected there to be more stops of African American drivers, such stops occur. The high degree of explained variance bodes well for the identification of outlier block groups. We now turn to that analysis.

Table 19. Regression Analysis of Number of African Americans Stopped in Vehicles in Census Block Groups

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 82.5%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-.573	4.911		-.117	.907		
# White Driver Vehicle Stops	.318	.022	.378	14.519	.000	.706	1.416
# Resident Population	-.013	.003	-.141	-5.170	.000	.647	1.545
# African American Resident Population	.066	.006	.347	10.852	.000	.467	2.142
# Incivility Calls for Service	.419	.112	.116	3.752	.000	.501	1.996
# of African Am. Drivers in Accidents	.502	.054	.275	9.324	.000	.549	1.823
# Successful Consent Searches in Vehicle Context	9.607	1.382	.218	6.951	.000	.487	2.052

Similar to the analysis of pedestrian stops, we use the model in Table 19 to generate predicted values of the number of vehicular stops of African Americans for each of the 366 block groups for which we have complete data. Figure 2 shows the relationship between the predicted values and the observed values of number of African Americans stopped in vehicles. We find that residual values vary from -196 to +232. Thus, the positive outliers reach a higher range of observations than the negative outliers. Twelve block groups have more African Americans stopped in vehicles in year 2002 than the model predicted (that is the values lie outside the 95% confidence interval), while nine block groups have negative values below that confidence interval. Again whether these counts are “excessive” or not is difficult to determine.

Figure 2. Predicted and Observed Number of African American Drivers Stopped



Evaluating Outliers: Number of African Americans Stopped in Vehicular Context

The positive outliers in the model of African American vehicular stops could be accounted for by factors other than those controlled for in our model. One such factor could be the presence of a major road or street (thoroughfare) through a census block group. Where such a thoroughfare is present and involves a link between predominantly African American districts, there may be more stops of African Americans than our model predicts. (However, for this explanation to be valid we would also have to assume that the thoroughfare has relatively few accidents, else the prevalence of African Americans in accidents would be accounting for African American presence.)

We presented a map of the positive and negative outliers to police leadership in the districts involved. They provided the following possible explanations for the positive outliers: 1) checkpoint activity (set up of a vehicle check point); 2) a rash of accidents in an area resulted in more patrolling; 3) presence of major north-south and of east-west thoroughfares; 4) proximity to the coliseum; 5) presence of a police substation; and 6) "crackdown" area where drivers are "stopped for everything" because of erratic driving.

As for the negative outliers of African American vehicular stops, the police leadership suggested: 1) prevalence of "service roads" rather than thoroughfares; 2) prevalence of "dead-end" roads (thus traffic is perceived to be limited and access to the area by the police is also limited); 3) area with predominantly white commuters; 4) presence of a predominantly Asian and an Hispanic population; and 5) presence of a large shopping center (with private security). Similar to pedestrian stops, the police leadership was somewhat puzzled about how some of the negative outliers would be accounted for. Nor is it obvious why a particular factor, independent of the six variables in the model

(Table 19) would necessarily account for high or low counts of stops of African American vehicles. However, the factors cited were thought to be unique attributes of these areas, and thus these factors might affect the count of the number of African Americans stopped in vehicles.

Summary of Pedestrian and Vehicular Stop Findings

Thus far, we have developed models of the processes that are found to explain why both pedestrian stops and vehicular stops occur. We have shown that pedestrian stops seem to be determined by demand (911 calls) and by success (contraband found in a search). For vehicular stops, more factors are involved, including the residential demographic composition and the people likely to be on the highway – as evident by the demographic characteristics of drivers in accidents. Of the many reasons why citizens call for service, we have found that calls for incivility offenses (prostitution, drugs, fighting, and drunken pedestrians) are the most important in determining the presence of the police in conducting stops (particularly pedestrian stops).

In examining police activity for particular areas, we have identified several areas with a high number of pedestrian stops of African Americans, and several areas with a high number of vehicular stops of African Americans. Whether or not these positive outliers are "excessive" relative to the goals and objectives of the CMPD we cannot say. There are factors that lie outside of our models that could account for the positive outliers. Similarly, there are factors not included in our models that may be accounting for negative outliers. We will continue to discuss the nature and extent of the departures from the model's prediction with CMPD leadership and with the advisory committee to help them in making a determination of how plausible these factors are as explanations.

Pedestrian Stops Resulting in Searches

Charlotte-Mecklenburg police reported a total of 6,229 pedestrian stops in 2002. The majority of people stopped and questioned by the police were African American males (64%) followed by white males (20%). Most of the people stopped and questioned were African American (72%), male (85.5%), Charlotte-Mecklenburg residents (89%) and the average age was 30.

The question we address here is whether African Americans are subject to an excessive number of searches. This is a particularly difficult question because we lack data on the circumstances under which the police made the decision to "look at" the pedestrians, and we lack data on what the police saw or heard that led them to believe that a request for a search was appropriate, given the circumstances. Searches where an officer requests permission to search are called "consent searches" and make up the majority of all searches conducted of pedestrians who are stopped for questioning (Table 20). Note that we exclude requests for a search in which there was a probable cause to conduct a search, and we exclude searches incidental to an arrest (for which there is also probable cause). It is with consent searches that suspicion of racial profiling is most likely, since the other types of searches (probable cause, search incidental to an arrest) minimize discretion on the part of the officer. (We omit from consideration the "protective frisks" since they are very small in number).

Officers reported in a "free field" format some of the reasons for the stop and for conducting a search. A sampling of those comments are reported in Appendix A of this report. While the reported reasons for the stop varied, one can see that frequently the pedestrian is someone who is in an area known for drug transactions.

Table 20. Type of Search Conducted After Pedestrian Stop

	Frequency	Percent	Valid Percent	Cumulative Percent
No Search	2387	38.3	38.3	38.3
Consent	2232	35.8	35.8	74.2
Probable Cause	407	6.5	6.5	80.7
Protective Frisk	251	4.0	4.0	84.7
Search Incident to Arrest	939	15.1	15.1	99.8
Search Warrant	13	.2	.2	100.0
Total	6229	100.0	100.0	

An important question regarding consent searches is whether police are more effective in finding contraband among African Americans or whites. If there is a large difference in the successful searches of whites versus African Americans, and success rates are lower for the latter, this could be construed as evidence of racial or arbitrary profiling. Table 21 shows that they are more effective in finding contraband among whites subject to a consent search. We also hypothesized that the context in which the consent searches were asked for and conducted might influence the success rate of finding contraband. Specifically, we hypothesized that where consent searches were conducted in the context of a higher number of incivility calls for service (a measure of context and a variable that we found to be the strongest predictor of pedestrian stops in the analysis above), there would be a lower success rate in finding contraband. That is, where searches are more prevalent, the police would be less successful in finding contraband since the net was being "cast wider" because of the demand for policing in those neighborhoods.

The results in Table 21 generally confirm our hypothesis. In neighborhoods with low and medium levels of incivility calls for service (as defined as the lowest third and middle third, of the count of neighborhood incivility calls for service, respectively),[53] we find that the success rates are higher than in neighborhoods with high levels of incivility calls for service (upper third).[54] That is, the areas – and by implication, the circumstances in which African Americans suspects are observed -- may more often be in the vicinity of problem neighborhoods (often with "drug houses" or areas known for street drug exchanges).

Notice that the success rate is very high for searches of whites in low incivility neighborhoods (41.6%), and very low for whites in neighborhoods with high incivilities (11.7%). For African Americans the success rate is more evenly distributed, varying from 25.8% in the medium incivility level neighborhoods, to 23.3% in the low incivility neighborhoods, to a low of 19.9% in the high incivility neighborhoods. It should also be noted that the type of neighborhood with the most consent searches conducted are the ones with the high levels of incivilities (e.g., 515 consent searches of African Americans are conducted in high incivility neighborhoods, compared to 362 in low incivility neighborhoods).

It is difficult to determine whether or not the evidence in Table 21 should be interpreted as supporting the hypothesis that there is racial bias in the decision to request

[53] Lowest level of incivility neighborhoods are those with zero to 28 calls for incivility offenses in 2002; medium 29 to 69; high 70 or more.
[54] We define consent searches to be only those searches with a legal basis -- as defined by the police officer filling out the stop form -- of "reasonable suspicion" or simply "searches pursuant to consent" as consent searches, excluding some searches which were classified as consent searches but which are listed as having a probable cause legal basis. Also, only geocoded cases appear in the table.

a search. On the one hand, clearly African Americans -- once subjected to consent searches -- are more often found not to have contraband than are whites. We have suggested that this may have to do with the volume of searches in high incivility neighborhoods. However, in such neighborhoods African Americans are more likely to have contraband than are whites who are consent searched in the same type of neighborhoods. Thus, where we would expect there to be the highest level of "inefficiency" in the searching of African Americans (where searches are most likely to occur), we find that although the success rate is lower than in less "troubled" neighborhoods " (e.g., where there are fewer incivility offenses), it is still higher than observed for whites in highly troubled neighborhoods.[55]

To more fully understand what accounts for the searching of African Americans in the pedestrian context, we should also take into consideration time as well as place. For example, in Figure 3 below we show the number of consent searches resulting from pedestrian stops by time of day. We distinguish those pedestrian consent searches where contraband was found from those where it was not found. An interesting pattern emerges. The number of consent searches peaks in the late afternoon between 16:00 and 17:00 (4 to 5 pm), and then drops off (probably due to the fact that police are typically involved in other activities associated with rush hour traffic, including attending to accidents and filling out accident reports), only to rise again to peak around midnight. Notice, however, that the number of successful searches (defined as searches resulting in contraband being found) does not rise proportionately to the number of consent searches

[55] We suspect that one reason why whites may have a low rate of contraband detection in high incivility neighborhoods may be due to their being a minority in some of the high incivility neighborhoods (although many of these neighborhoods are mostly white neighborhoods – analysis not shown here).

being conducted. This suggests an inefficiency in consent searches at the times of the day when, ironically, most of the successful searches are conducted.

A question to be asked is whether the inefficiency in searches can be justified from an organizational perspective. For example, it is the case that increased pedestrian traffic in the late afternoon and early evening hours coincide with an increase in incivility calls for service. (See Appendix E for confirmation of this claim). As earlier, we again ask here whether the response to the added pedestrian traffic in the evening and night hours (including those pedestrians with contraband) can be justified (again see Appendix F for a discussion of alternative models with logged dependent variables). That is, should the police response be one characterized by a proportionately higher response than called for by the contraband-finding success rate? As researchers, we cannot say whether the relative inefficiency in finding contraband is an acceptable by-product of the increase in the number of problems during the peak hours of drug transportation. Given that it seems clear that the number of consent searches varies with place and time, we turn to a more formal model of the number of such searches of African Americans.

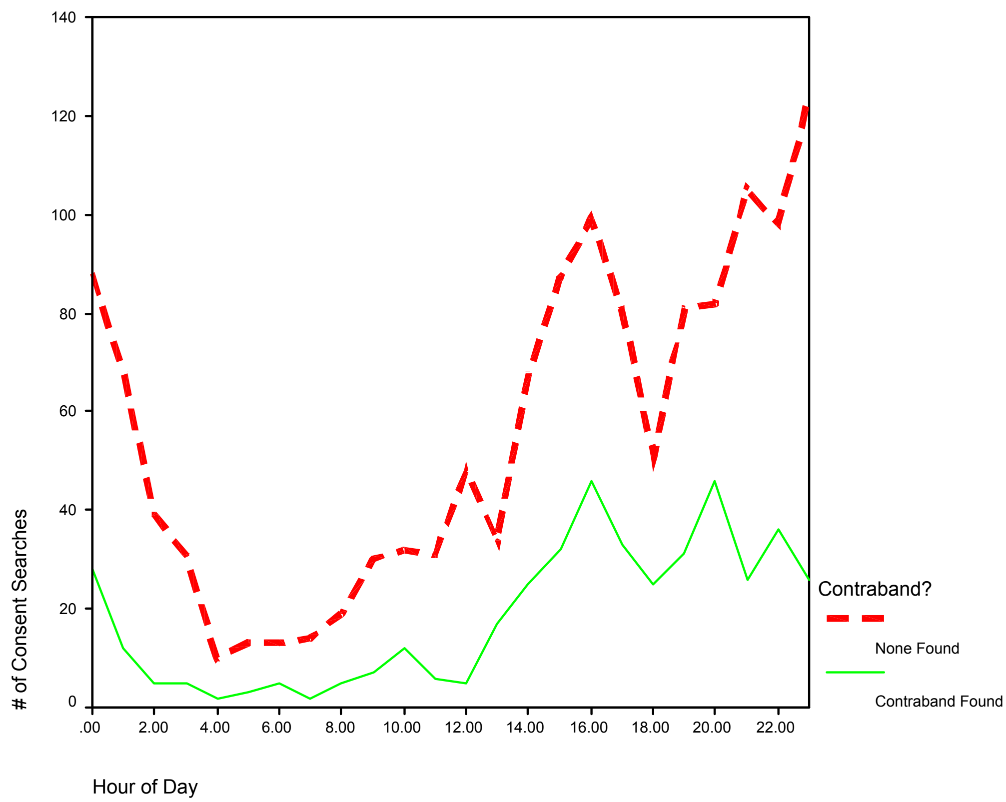
In Table 22 below we show several models of the number of consent searches of African Americans at the census block group level. In Model One, we show that, as expected, the number varies as a function of the number of incivility calls for services (by citizens). We also include in the model the number of white consent searches (entered in the model as a crude statistical control for the volume of consent search activity in a block group) – despite the fact that the variable does not reach statistical significance.

Most of the variance in the number of consent searches of African Americans, however, remains unexplained.

Table 21. Success of Pedestrian Consent Searches by Race/Ethnicity and Degree of Incivility Calls for Service in Neighborhood Context

Context	Contra-band Found?		Race/Ethnicity						Total
			Asian	Af. Am.	Hisp.	Ind.	Unk.	White	
Neigh-borhood with Low # of Incivility CFS	No	Count	2	303	25		2	73	405
		% within Contra Found	.5%	74.8%	6.2%		.5%	18.0%	100.0%
		% within RACE	100.0%	76.7%	69.4%		66.7%	58.4%	72.2%
	Yes	Count	0	92	11		1	52	156
		% within Contra Found	.0%	59.0%	7.1%		.6%	33.3%	100.0%
		% within RACE	.0%	**23.3%**	30.6%		33.3%	**41.6%**	27.8%
	Total	Count	2	395	36		3	125	561
		% within Contra Found	.4%	70.4%	6.4%		.5%	22.3%	100.0%
		% within RACE	100.0%	100.0%	100.0%		100.0%	100.0%	100.0%
Neigh-borhood with Medium # Incivility CFS	No	Count	2	362	16	2	1	73	456
		% within Contra Found	.4%	79.4%	3.5%	.4%	.2%	16.0%	100.0%
		% within RACE	100.0%	74.2%	72.7%	100.0%	50.0%	67.0%	73.0%
	Yes	Count	0	126	6	0	1	36	169
		% within Contra Found	.0%	74.6%	3.6%	.0%	.6%	21.3%	100.0%
		% within RACE	.0%	**25.8%**	27.3%	.0%	50.0%	**33.0%**	27.0%
	Total	Count	2	488	22	2	2	109	625
		% within Contra Found	.3%	78.1%	3.5%	.3%	.3%	17.4%	100.0%
		% within RAC	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Neigh-borhood with High # Incivility CFS	No	Count		415	13	1	3	53	485
		% within Contra Found		85.6%	2.7%	.2%	.6%	10.9%	100.0%
		% within RACE		80.1%	76.5%	50.0%	100.0%	88.3%	80.8%
	Yes	Count		103	4	1	0	7	115
		% within Contra Found		89.6%	3.5%	.9%	.0%	6.1%	100.0%
		% within RACE		**19.9%**	23.5%	50.0%	.0%	**11.7%**	19.2%
	Total	Count		518	17	2	3	60	600
		% within Contra Found		86.3%	2.8%	.3%	.5%	10.0%	100.0%
		% within RACE		100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

Figure 3. Number of Consent Searches in Pedestrian Context by Hour of the Day: Contraband Found or Not



In Model Two of the same table, we allow other variables that characterize the census block groups to enter the equation (essentially the same pool of variables as tested in the earlier models for number of pedestrian stops). Here, the statistically significant variables added from Model One include: number of calls for service for assaults, residents aged 22-29, and number of African American residents. The variance explained increases to 51.2%. In Model Three, we let hour of the day of the pedestrian stops enter the model (i.e., the number of pedestrian stops for each hour), with variables for every hour of the day except noon hour (the referent category). Three hours are shown,

Table 22. Regression Models of Number of African American Pedestrian Consent Searches

	MODEL ONE	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	R^2 = .482	B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-.291	.619		-.470	.639		
	# White Consent Searches	.640	.335	.094	1.910	.057	.778	1.286
	# Incivility Calls for Service	.217	.016	.648	13.202	.000	.778	1.286

	MODEL TWO	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	R^2 = .512	B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.673	1.202		-1.392	.165		
	# White Consent Searches	.979	.340	.143	2.877	.004	.711	1.406
	# Incivility Calls for Service	.183	.018	.545	10.066	.000	.603	1.657
	# Assault Calls for Service	.848	.431	.102	1.969	.050	.661	1.514
	# African American Residents	.002	.001	.119	2.045	.042	.526	1.903
	# Residents 22-29 Yrs Old	-.006	.002	-.140	-2.757	.006	.684	1.462

	MODEL THREE	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	R^2 = .827	B	Std. Error	Beta			Tolerance	VIF
	(Constant)	-1.120	.715		-1.566	.118		
	# White Consent Searches	-.165	.213	-.024	-.776	.438	.645	1.551
	# Incivility Calls for Service	.011	.014	.031	.767	.444	.374	2.670
	# Assault Calls for Service	.652	.257	.078	2.533	.012	.654	1.530
	# African American Residents	.002	.001	.090	2.564	.011	.513	1.948
	# Residents 22-29 Yrs Old	-.003	.001	-.067	-2.163	.031	.646	1.547
	#Pedestrian Stops 6-7 am	4.211	.523	.259	8.059	.000	.606	1.651
	# Pedestrian Stops4-5 pm	1.373	.159	.364	8.615	.000	.351	2.850
	# Pedestrian Stops 11 to 12 pm	1.327	.115	.396	11.567	.000	.534	1.872

Table 22 (Continued)

	MODEL FOUR	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	$R^2 = .531$	B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	-1.462	1.161		-1.259	.209		
	# Incivility Calls for Service	.203	.015	.604	13.150	.000	.804	1.244
	# Assault Calls for Service	.752	.387	.090	1.943	.053	.786	1.273
	# Residents Ages 22-29	-.004	.002	-.089	-2.113	.035	.962	1.040
	Success Rate of African American Consent Searches	19.690	4.188	.210	4.702	.000	.854	1.171

although more actually entered the equation before the collinearity diagnostics revealed that there was excessive multi-collinearity: number of pedestrian stops between 6 and 7 am, 4 to 5 pm, and 11 pm -12 midnight. We stopped allowing the variables to enter the equation as they seemed to be redundant with variables in the equation already (i.e., differing by only an hour) and also these variables seemed to be dominating the results (e.g., making other variables in the model statistically insignificant), and thus clouding the interpretation of the findings. We find that we can explain 82.7% of the variance in the number of consent searches of African Americans by including the volume of all pedestrian stops during these three hours.[56]

Note that we include the hours representing the frequency of the pedestrian stops not to "explain away" racial disparity, but rather to account for the timing of the consent

[56] These results are somewhat complicated by the multi-collinearity with other hours proximate in time. Thus, the fact that there are more consent searches of African Americans between the hours of 11 and 12 noon does not mean that there is no such tendency between the hours of 10 and 11. In fact, the hours proximate in time to the hours in the table could substitute almost as well as the hours shown, but due to their conceptual redundancy and multicollinearity with other variables in the equation, they are not entered into the equation shown here.

searches of African American pedestrians.[57] Just as the police search African American citizens in some areas of the city more so than others, so do they search African American pedestrians more so at some times of day than at others.[58] It is interesting to note that the results suggest a tendency to patrol and engage citizens (and, as a consequence, to conduct a pedestrian stop and a possible search) during non-rush hour times, which are the times that a U.S. Department of Transportation survey (1977) indicates African Americans are more likely to initiate travel/trips.

It could also be argued that these hours correspond to hours of drug sale activities, as the calls for service for drugs show that such calls occur disproportionately at similar times (see Appendix E). Thus, observing late morning, mid-afternoon, and late evening searches for contraband is not surprising.

The implication of the analysis of time and place above for our understanding of disparity in the pedestrian consent searches and in the lower rate of success in finding contraband among African American citizens is that volume of searches and efficiency are inversely related. African Americans may be searched more often in the inefficient context of neighborhoods with high levels of incivility problems and at times of day that are conducive to the police conducting patrols with pedestrian consent searches as a goal. This is not meant to serve as a justification for the relatively high search rate -- nor low success rate -- of African American pedestrian searches, but rather the analysis represents a specification of where and when such searches occur. Thus, if it were to be determined

[57] It is interesting to note the apparent significance of these specific times of day as they coincide with a regional travel survey of southeastern United States (US Department of Transportation, 1997). Results from this survey show times of the day when African Americans are generally more likely to be on the highways (and presumably on the sidewalks): afternoon, late evening and very early in the morning. Thus, it is likely that the finding in Table 22 can partly be explained by activity levels of citizens walking outdoors, as well as the activity levels of the police who encounter pedestrians more often during certain hours of the day.

[58] Of course, there is a built in correlation between the number of African Americans in consent searches and the number of consent searches in any given hour, since the latter is included as part of the former. This in part accounts for the very high variance explained in the equation of 82%.

that the number of consent searches of African Americans were excessive, then we would have an indication as to where and when they might be reduced. On the other hand, if they are not deemed excessive, we would have a possible explanation for the seemingly disparate number of searches and failed searches: the degree of response to problem areas (in part attributable to the idea of targeting high risk neighborhoods) and a "bunching" of searches at certain times of the day/night.

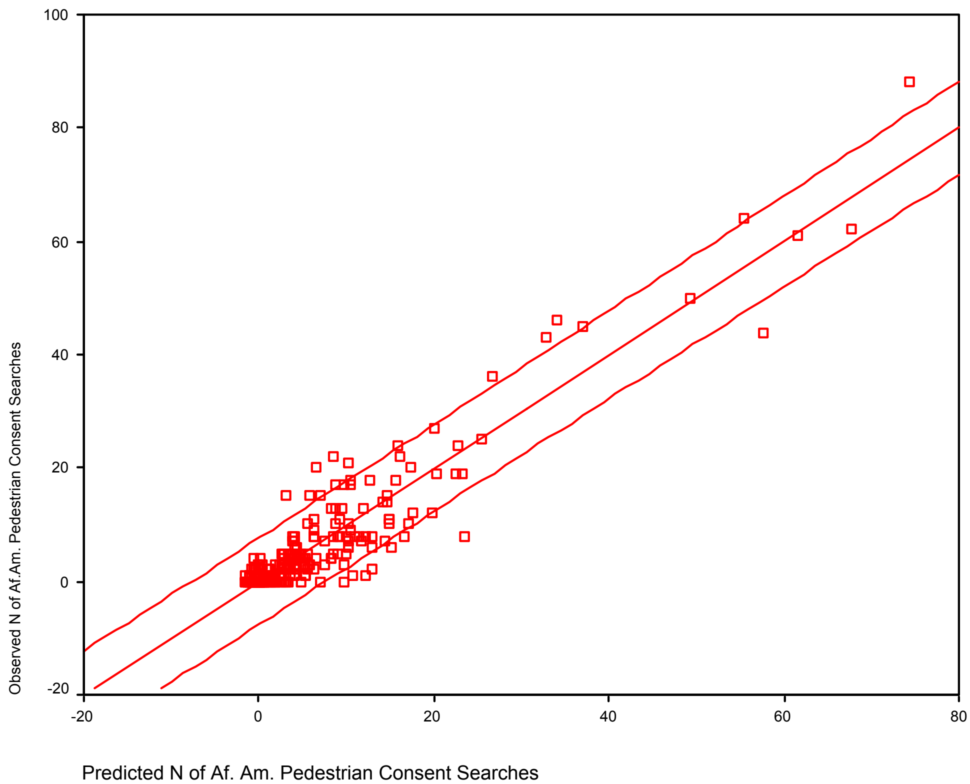
In our earlier models of pedestrian and vehicular stops, we were also interested in determining whether the success of consent searches was a factor in the models of number of African Americans stopped. Here too, we would hypothesize that the number of consent searches might increase with the success of those searches turning up contraband. Model Four shows the results of including the success rate of consent searches of African Americans. The coefficient is statistically significant and is moderately related to the number of pedestrian consent searches.[59] The hour of day variables are excluded from the equation from Model Three are excluded from the equation as they are collinear with the success rate of African American consent searches.

Finally, we address the question of which census block groups are positive and which are negative outliers, relative to a model of the number of African American consent searches. We show in Figure 4 the predicted and observed values based on the regression equation and findings reported in Table 22 above. However, here we have combined Models Three and Four, and included 3 additional time periods (2-3 pm, 8-9 pm and 10-11 pm). The model now includes some time of day measures (number of

[59] Unlike in the earlier models we include here a success rate (number of times drugs or alcohol found divided by the number of consent searches of African Americans). A separate model not reported here in the table shows that the count variable of number of successful discoveries of drug and alcohol contraband dominates the equation, making other variables statistically insignificant.

pedestrian stops for the 3 hours just mentioned) and the "hit rate" for African Americans subject to consent searches as pedestrians. We define as an outlier any census block group outside of the 95% confidence range of the predicted values.[60]

Figure 4. Predicted Number of African American Consent Searches in Pedestrian Context by Observed Number



Several positive outliers lie just above the confidence interval and several below. Note that the "distance" from the predicted values (the middle line of the three diagonal lines in the figure) is relatively small in magnitude, as there are relatively few consent searches as compared to pedestrian stops as analyzed earlier in the report. Thus a positive outlier

[60] Thus, we include time of day measures such as those in Model Three even though it is true that the decision to stop and search an African American pedestrian must occur in time, and thus we risk under-estimating positive outliers by including time of day in the identification of particular census block groups as excessively disparate.

here represents only a few consent searches more than what would be expected for a specific census block group.

Evaluating Outliers: Number of African Americans Searched in Pedestrian Context

As for what possibly accounts for the positive and negative outliers for consent searches in the pedestrian context, we, as researchers, thought it may be, as discussed earlier for pedestrian stops, movement of the drug market from a particular neighborhood such that the success rate of searches would be consequently lowered, leading to an excessive number of African Americans searched in these mostly African American neighborhoods. Also, we thought is possible that a small local flare up in the drug market might bring about a quick response in the form of increased consent searches (with the goal of "nipping the problem in the bud") that statistically might be disproportionate (in a linear, additive sense) to the calls for service in the area. As for negative outliers we did not have any tentative hypotheses.

The local police leadership mentioned some of the same factors discussed above for outliers in the number of African American pedestrian stops. As for African American consent searches, these possible explanations for the positive outliers were mentioned: 1) proliferation of street prostitutes in an area such that searches were often less likely to find contraband; and 2) an aggressive drug enforcement area.[61] As for negative outliers for African American pedestrian searches: 1) presence of a large cemetery; 2) "lightening rod" effect of adjacent hot spot neighborhood that draws police

[61] Presumably the lower hit rate in an area of aggressive enforcement could be justified on the grounds that avoiding other social costs (such as the deteriorization of a neighborhood) are important.

resources; 3) local shopping center with private security;[62] and 4) possible underreporting of stops and searches by some police officers.[63]

In summary, the evaluation of the consent searches in the pedestrian context reveals that a relatively high number of African Americans are searched, and that the success rate of finding contraband is lower than among whites. Both time and place are relevant to our understanding of why these rates of consent searches are higher for African Americans. In that police are responding to incivility crimes as a direct, linear and additive function of the presenting problems of those neighborhoods (incivilities), their searches may be excessive in some areas and deficient in others.

Pedestrian stops seem to be occurring for African Americans more so at some times of day than others, and those times may correspond with greater police availability for conducting searches. For example, these times of day may be when there are fewer vehicular accidents, or perhaps at times of day when street drug trafficking is more common. As stated previously, whether or not the degree of police searching of African Americans is "excessive" or racially biased is beyond the scope of this research, but we have supplied data and findings that should help police leadership and the citizen advisory board for this project make a determination.

Consent Searches at Traffic Stops

We now turn our attention to consent searches resulting from a vehicular stop. In Table 23 we see that African Americans constitute 65.4% of all those who are subjected

[62] Also, the factors mentioned for negative outliers for African American pedestrian searches were also referred to.
[63] While the underreporting is possible, in the early phases of our research we compared the citation records with the stop records that indicated that a citation was issued and found that the stop records were quite complete. However, it is possible that some stop forms resulting in searches are not being completed.

to a consent search.[64] Roughly, one of every 20 (five of every 100) stopped vehicles that are driven by an African American is subject to a consent search. In Table 24 we see that generally both the driver and the vehicle are subject to a search. However, in some cases only one or the other is searched (e.g., in 406 instances, or 14.5 % of the consent searches, only the vehicle was consent searched).

Table 23. Prevalence of Consent Searches Resulting from Vehicular Stop by Race/Ethnicity (Geocoded Cases)

Consent Search?		Race/Ehnicity						Total
		Asian	Af. Am.	Hispanic	Indian	Unk.	White	
No	Count	1249	30789	8167	63	1359	32777	74404
	% within Consent Search	1.7%	41.4%	11.0%	.1%	1.8%	44.1%	100.0%
	% within Race/Ethnicity	97.8%	94.5%	96.9%	96.9%	97.6%	98.1%	96.5%
Yes	Count	28	1779	261	2	33	618	2721
	% within Consent Search	1.0%	65.4%	9.6%	.1%	1.2%	22.7%	100.0%
	% within Race/Ethnicity	2.2%	5.5%	3.1%	3.1%	2.4%	1.9%	3.5%
Total	Count	1277	32568	8428	65	1392	33395	77125
	% within Consent Search	1.7%	42.2%	10.9%	.1%	1.8%	43.3%	100.0%
	% within Race/Ethnicity	100.0%	100.0%	100.0%	100.0%	100.0 %	100.0%	100.0%

In only 5.3% of the cases where there was there a consent search in the vehicular context with no search of the vehicle. It should also be noted that there are somewhat more consent searches resulting from the stop of a vehicle than from a pedestrian stop (compare with Table 20).

[64] N.B. this is of geocoded observations. African Americans compose 64.3% of all consent searches.

Table 24. Search of Person or Vehicle, Consent Searches Resulting From Vehicular Stops*

	Person Searched In Consent Search?		Vehicle Searched in Consent Search? No	Vehicle Searched in Consent Search? Yes	Total
	no	Count	10	509	519
		% within Person searched	1.9%	98.1%	100.0%
		% within Vehicle Searched	6.9%	19.8%	19.1%
	Yes	Count	134	2068	2202
		% within Person Searched	6.1%	93.9%	100.0%
		% within Vehicle Searched	93.1%	80.2%	80.9%
Total	Count		144	2577	2721
	% within Person Searched		5.3%	94.7%	100.0%
	% within Vehicle Searched		100.0%	100.0%	100.0%

*In only a few instances was the driver not searched, but a passenger was.

As with pedestrian searches, a crucial question is the success rate. We can see in Table 25, contraband is found about 25.4% of the time in a vehicular search (somewhat higher than with pedestrian consent searches), but the rate is lower among African Americans than whites (24.2% versus 30.9%). As in the case with pedestrian consent searches, the rate of successfully finding contraband is lower among African Americans than whites. This again raises the question of why there would be a lower rate of success. The disparity may be attributed to bias. It may be useful, however, to see how the success rate varies across neighborhoods and time of day. Again, we look to see if the neighborhood context and the time of day when searches are typically conducted play a role in accounting for the number of consent searches of African Americans. As with

Table 25. Contraband Found by Race/Ethnicity of the Driver in Consent Searches

Contra-band Found?		Race/Ethnicity						Total
		Asian	Af. Am.	Hispanic	Indian	Unk.	White	
No	Count	19	1348	207	2	28	427	2031
	% within Contraband Found	.9%	66.4%	10.2%	.1%	1.4%	21.0%	100.0%
	% within Race/Ethnicity	67.9%	75.8%	79.3%	100.0%	84.8%	69.1%	74.6%
Yes	Count	9	431	54	0	5	191	690
	% within Contraband Found	1.3%	62.5%	7.8%	.0%	.7%	27.7%	100.0%
	% within Race/Ethnicity	32.1%	**24.2%**	20.7%	.0%	15.2%	**30.9%**	25.4%
Total	Count	28	1779	261	2	33	618	2721
	% within Contraband Found	1.0%	65.4%	9.6%	.1%	1.2%	22.7%	100.0%
	% within Race/Ethnicity	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

pedestrian stops, we aggregate the data to the census block group level. Table 26 shows that African American drivers stopped and subject to a consent search are somewhat more likely to have contraband found on them if the neighborhood is medium in level of incivility calls for service by citizens, than if the neighborhood (census block group) has a high or low level of incivilities.[65] Unlike what was observed earlier, we notice that there is very little difference in the white hit rate across neighborhoods varying in incivility calls for service (31.7%, 29.8%, and 31.3% for low, medium and high incivility levels). For African American the lowest success rate in finding contraband occurs in the low incivility neighborhoods (12.9%) and highest in the medium incivility neighborhoods.

[65] As earlier in the report, low levels are defined as in the lower third, medium in the middle third, and high in the upper third of the number of incivility calls for service in a census block group.

Table 26. Contraband Found by Race/Ethnicity and Incivility Level of Neighborhood at Searches During Vehicle Stops

	Contraband Found?		Race/Ethnicity Asian	Af. Am.	Hispanic	Indian	Unk.	White	Total
Neigh-borhood with Low # of Incivility Calls for Service	No	Count		27	5		2	28	62
		% within Contraband Found		43.5%	8.1%		3.2%	45.2%	100.0%
		% within Race/Ethnicity		87.1%	100.0%		66.7%	68.3%	77.5%
	Yes	Count		4	0		1	13	18
		% within Contraband Found		22.2%	.0%		5.6%	72.2%	100.0%
		% within Race/Ethnicity		**12.9%**	.0%		33.3%	**31.7%**	22.5%
	Total	Count		31	5		3	41	80
		% within Contraband Found		38.8%	6.3%		3.8%	51.3%	100.0%
		% within Race/Ethnicity		100.0 %	100.0%		100.0 %	100.0%	100.0%
Neigh-borhood With Medium # of Incivility Calls for Service	No	Count	5	192	33	1	5	134	370
		% within Contraband Found	1.4%	51.9%	8.9%	.3%	1.4%	36.2%	100.0%
		% within Race/Ethnicity	55.6%	72.2%	70.2%	100.0 %	83.3%	70.2%	71.2%
	Yes	Count	4	74	14	0	1	57	150
		% within Contraband Found	2.7%	49.3%	9.3%	.0%	.7%	38.0%	100.0%
		% within Race/Ethnicity	44.4%	**27.8%**	29.8%	.0%	16.7%	**29.8%**	28.8%
	Total	Count	9	266	47	1	6	191	520
		% Contraband Found	1.7%	51.2%	9.0%	.2%	1.2%	36.7%	100.0%
		% within Race/Ethnicity	100.0 %	100.0 %	100.0%	100.0 %	100.0 %	100.0%	100.0%
Neigh-borhood with High # of Incivility Calls for Service	No	Count	14	1129	169	1	21	265	1599
		% within Contraband Found	.9%	70.6%	10.6%	.1%	1.3%	16.6%	100.0%
		% within Race/Ethnicity	73.7%	76.2%	80.9%	100.0 %	87.5%	68.7%	75.4%
	Yes	Count	5	353	40	0	3	121	522
		% within Contraband Found	1.0%	67.6%	7.7%	.0%	.6%	23.2%	100.0%
		% within Race/Ethnicity	26.3%	**23.8%**	19.1%	.0%	12.5%	**31.3%**	24.6%
	Total	Count	19	1482	209	1	24	386	2121
		% within Contrband Found	.9%	69.9%	9.9%	.0%	1.1%	18.2%	100.0%
		% within Race/Ethnicity	100.0 %	100.0 %	100.0%	100.0 %	100.0 %	100.0%	100.0%

Thus, there is some qualified support for the hypothesis that the success rate of finding contraband would be lower for African Americans where there are relatively many searches and where the incivility level is high (contraband is found in only 25.4% of the vehicular consent searches). However, this is a considerably lower contraband hit rate found for African Americans in low incivility neighborhoods (12.9%). We do not know why the hit rate is so low in low incivility neighborhoods, however it is possible that these are mostly white neighborhoods, and that African Americans in these mostly white neighborhoods are viewed with suspicion by the police. The African Americans may be viewed as "out of context".[66]

Figure 5 shows that, again, there is a tendency for the contraband success rate to decline with the volume of consent searches across the hours of the day. In general, the closer the hours to midnight, the less efficient are the consent searches in finding contraband at vehicular stops. The relative lack of efficiency is also high in the late afternoon hours.

Interpreting the success rate across the hours of the day and across the neighborhoods we see that generally as the volume of searches increases the efficiency declines. However, despite the high volume of searches in high incivility neighborhoods, the success rate is not especially low. This perhaps indicates that the social ecology of the neighborhood has some predictive value as to whether or not a citizen subject to a consent search from a vehicular stop is likely to be in possession of contraband.[67]

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[66] Note, however, that this low hit rate is based on only 31 observations of African American consent searches in the vehicular context. Thus, there are relatively few such consent searches and the hit rate is somewhat unreliably estimated. Nevertheless, the percent African American in the low incivility block groups is on average only 6.5% whereas the percent white is these block groups is 89.3%.

[67] This is not to suggest that the social ecology factors should be used to make individual decisions about specific citizens.

Again, as stated earlier, we are not in a position to state whether the number of consent searches is excessive or not. However, to more formally assess the relative number of consent searches in census block areas, we again conduct a regression analysis of various characteristics of the census block group areas to see what factors are predictive of African American vehicular consent searches so as to more accurately assess whether they are excessive relative to the model's predictions.

In Table 27 we present the results of the regression analysis. Three models are shown. In Model One we present only two predictor variables, the number of vehicular consent searches of whites (as a control for the volume of consent search activity), and the number of calls for service for incivility offenses (which we found to be important in our models of pedestrian consent searches). Both are statistically significant and account for 56% of the variance in the number of African Americans consent searched at a vehicular stop. Thus, this model of vehicular consent searches of African Americans is similar to that of African American pedestrian consent searches.

In Model Two we let any additional predictor variable (from the same list of variables used for pedestrian searches) that is significant enter the equation (non-statistically significant ones are not entered into the equation). Here we see that the number of vehicular stops of African Americans, number of African American residents, and population aged 18 to 22 are added to the list of significant predictors, increasing the variance explained to 66%. Thus, we find that characteristics of the resident population are important to the likelihood than an African American will be subject to a consent search. Note that these results are not surprising in that -- net of the incivility calls for service -- the more African Americans in an area, the more African Americans we would expect to be subject to a consent search. Also, we hypothesized that the greater number of younger residents present the more likely a consent search would take place – but the results show just the opposite. Perhaps the number of young residents is measuring where there are apartment complexes and less vehicular traffic, but we are not sure.

Finally, in Model Three we allow variables measuring the volume of consent searches at each of the 24 hours of the day enter the equation.[68] We see by their omission from the table that reports only statistically significant predictors that -- unlike what we found for pedestrian searches -- that the times of day of the vehicular stops are unrelated to the number of African American drivers stopped and consent searched in the vehicular context.[69] Added to this model is the "hit rate" for African American consent searches in the vehicular context.[70] Note that the explained variance is 67%, somewhat more than what we found for pedestrian consent searches in a similar model (51.2%) – Model Two of Table 22. Among the most important predictor variables in Model 3 of Table 27 are: number of incivility calls for service (Beta = .462), number of vehicular stops of African Americans (.216) and number of African American residents (.182). The more residents 22-29 years old in an area, the fewer vehicular stops resulting in consent searches –

[68] Noon hour was arbitrarily chosen to be excluded from the regression equation and to serve as the referent category for the other hours.

[69] If we remove the variable "African American consent search hit rate" two time variables enter the equation with negative coefficients: 8-9 am and 6-7 pm, late rush hour times of day. This suggests to us a number of possible interpretations: during rush hour there is either less movement of drugs, less suspicious circumstances of drugs being moved in vehicles, or too little time to deal with drug movement since much time is spent dealing with accidents. The lack of time effects in general is perhaps not surprising in that searches represent a very small proportion of vehicular stops, and searches are presumably triggered by suspicious behavior or answers to questions in a way that is more "random" than what occurs in the case of pedestrian stops.

[70] We use the rate here (drug and alcohol successes divided by the number of consent searches in vehicular context) rather than the count of successes as the latter "dominates" the equation in the sense that it makes almost all of the other variables statistically insignificant (although number of incivilities and number of white consent searches in vehicular context remain statistically significant).

perhaps because this variable is measuring the presence of a type of neighborhood with less traveled streets.

Figure 5. Contraband Found or Not at Vehicular Consent Searches by Hour of Day

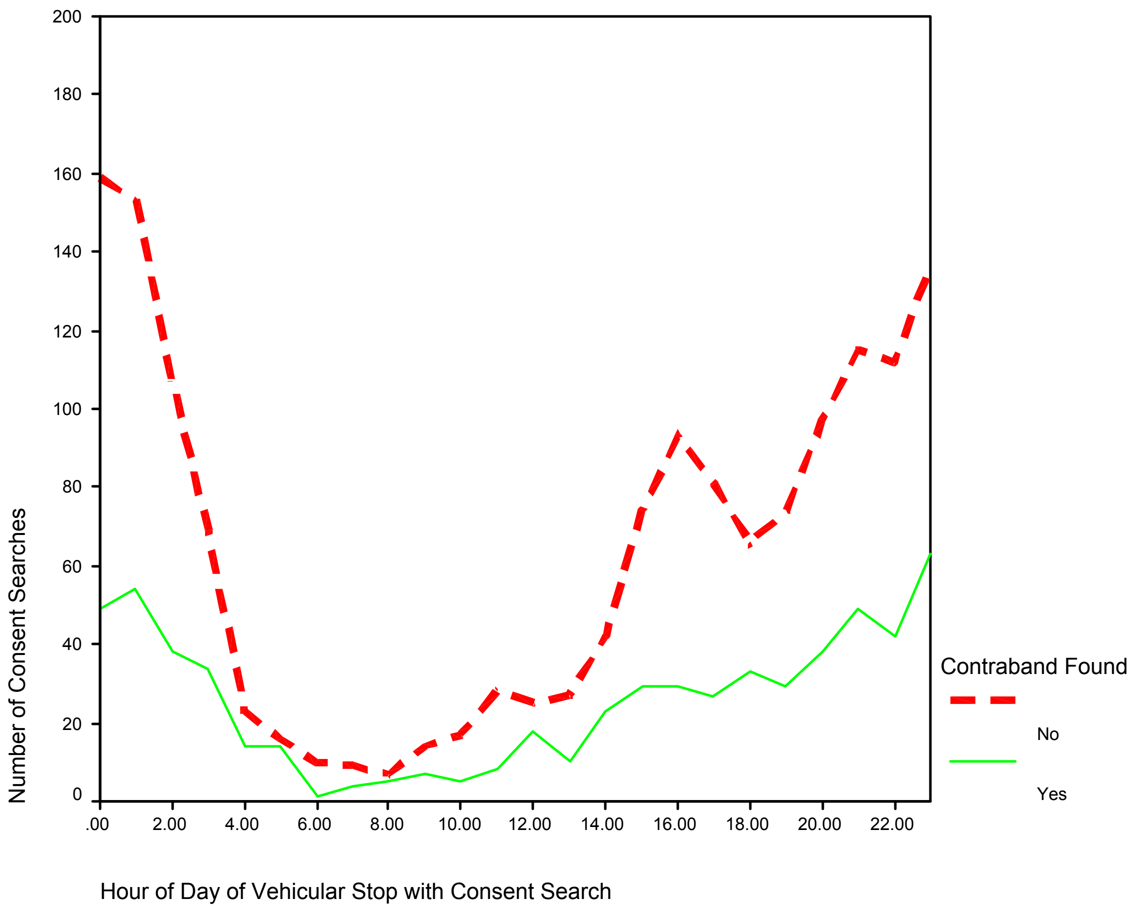


Table 27. Number of African Americans Consent Searched at a Vehicular Stop, Census Block Group Analysis (N=258)

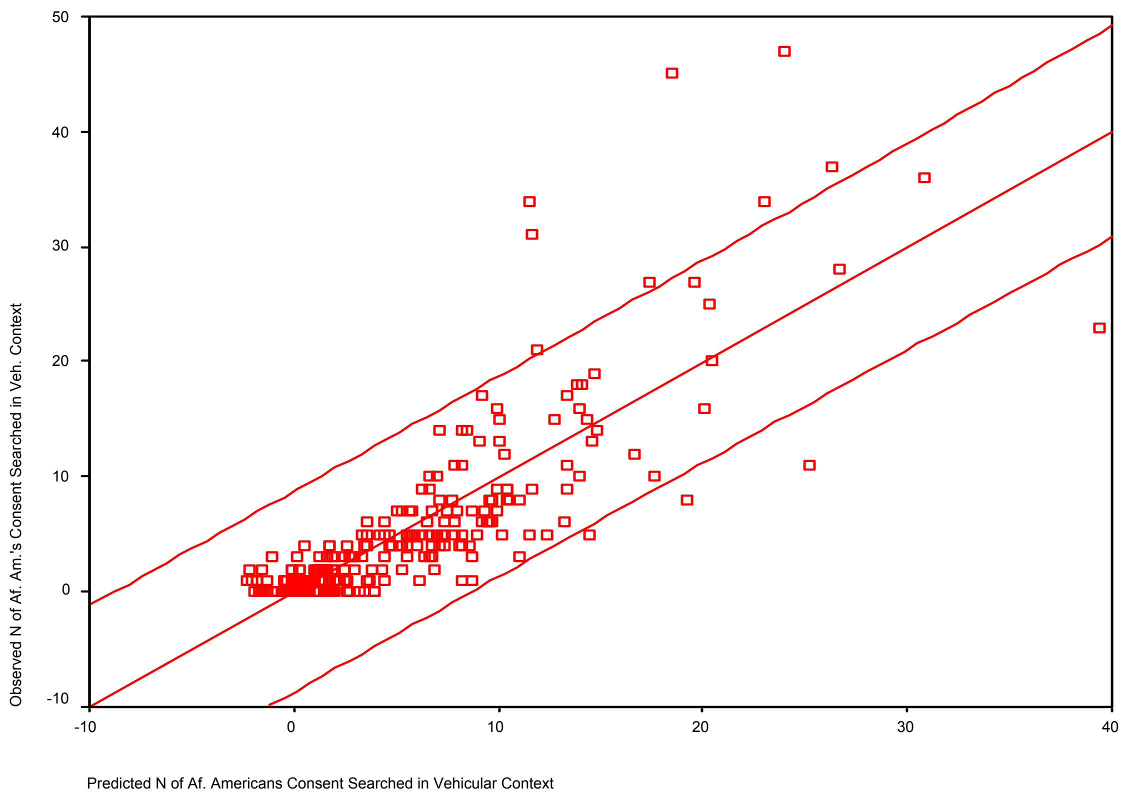
	Model One	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
	R^2 = .558	B	Std. Error	Beta			Tolerance	VIF
	(Constant)	.227	.444		.511	.610		
	# White Vehicular Consent Searches	.543	.119	.195	4.580	.000	.948	1.055
	# Incivility Calls for Service	.154	.010	.681	15.981	.000	.948	1.055
	Model Two							
	R^2 = .660	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
	(Constant)	-.043	.496		-.087	.931		
	# White Vehicular Consent Searches	.443	.109	.159	4.068	.000	.865	1.156
	# Vehicular Stops of African Americans	.017	.003	.266	5.158	.000	.497	2.010
	# Af. Am. Resident Population	.003	.001	.215	4.659	.000	.624	1.603
	# 18 to 22 yrs old	-.007	.001	-.249	-6.085	.000	.791	1.264
	# Incivility Calls for Service	.103	.010	.459	9.900	.000	.617	1.620
	MODEL THREE							
	R2 = .666	B	Std. Error	Beta	t	Sig.	Tolerance	VIF
1	(Constant)	-.174	.494		-.353	.724		
	# White Vehicular Consent Searches	.431	.108	.155	3.985	.000	.863	1.158
	# Vehicular Stops of African Americans	.014	.004	.216	3.907	.000	.424	2.356
	# Af. Am. Resident Population	.002	.001	.182	3.809	.000	.571	1.753
	# 22 – 29 yrs old	-.006	.001	-.222	-5.277	.000	.733	1.364
	# Incivility Calls for Service	.104	.010	.462	10.054	.000	.617	1.622
	Af. Am. Consent Search “Hit” Rate	5.396	2.296	.108	2.350	.020	.617	1.622

Figure 6 depicts the census block groups which have excessively high or low numbers of consent searches of African Americans in the vehicular context, as created from the results of the regression analysis for Model Three of Table 27. Recall that the variables in the model include demographic characteristics of the population, as well as incivility calls for service. The results look generally like what we saw with the pedestrian stops, with some census block groups having relatively high numbers of consent searches of African Americans and some relatively fewer (i.e., some above and some below the regression line depicted in the figure.) Note that here, in the case of consent searches of African Americans in the context of a vehicular stop, that there are fewer census block groups below the regression line in the lower right hand quadrant of the figure than in the upper right quadrant. Thus, there are only a few "negative" outliers in the figure, and relatively many positive ones.

Evaluating Outliers: Number of African Americans Searched in Vehicular Context

The local police leadership examined the locations of the positive outliers for African American searches in the vehicular context but did not have any new explanations beyond what was said earlier for other positive outliers. As for negative outliers of African Americans in the vehicular context, they mentioned: 1) presence of a research plaza; 2) a downtown area where searches were unlikely to be conducted due to the heavy pedestrian traffic on the streets; and 3) prevalence of new, small homes with many "dead end" streets.

Figure 6. Predicted and Observed Numbers of African American Consent Searches at Vehicle Stops, by Census Block Group



Summary and Conclusions

In general we have found that the prevalence in the number of stops of citizens in the pedestrian and in the vehicular contexts is not accounted for by the racial makeup of the census block groups with which the data were analyzed. The factors that generally account for the number of stops are factors associated with the demand (calls for service in the area) and success rate (number of successful consent searches). For vehicular stops, the results are similar to that found for pedestrian stops, with the number of drivers in accidents as the best predictor of the number of vehicular stops and the number of successful consent searches close behind. For neither vehicular stops nor for pedestrian stops is the racial make up of the population a factor in determining the number of such stops.

In general we find that the number of African Americans stopped and searched in the pedestrian context also varies with the incivility calls for service as well as the success rate of African American consent searches. The number of African American consent searches in the vehicular context, also varies as a function of the number of incivility calls for service in the same census block groups and is marginally affected by the success rate in consent searches in the vehicular context. Other factors, such as the number of vehicular stops of African Americans and the African American resident population size also affect the chances that an African American driver will be subject to a consent search. While such evidence in general justifies the volume of stops in both the pedestrian and vehicular contexts, it does not rule out the possibility that race is a factor in the decisions to stop a pedestrian or vehicle driver.

The analysis reveals that there are several areas with more stops of African Americans than the factors that we have identified as important would predict. Whether these are in fact areas where there are "excessive" stops of African Americans, we cannot say. In part the question's answer depends on whether the police response to problem neighborhoods is expected to follow a strict linear additive function of the number of calls for service in an area, or another function in which there is disproportionate responses to some areas because of their chronic crime problems (or at least with problems associated with "incivility" offenses). Again see Appendix F for a discussion.

The number of searches seems to vary as a function of the number of calls for service for incivility type offenses in both the pedestrian and the vehicular context. That is, where citizen demand is greatest for problems such as street prostitution, drugs, fighting, and drunken pedestrians, we find that the police are more likely to be conducting searches. The success rate of finding contraband is lower for African Americans, but seems to decline as a function of the volume of searches conducted. As the volume of searches conducted increases with time of day, and with the type of neighborhood, generally the success rate of finding contraband declines. Whether the generally lower success rate of finding contraband among African Americans is due to the presence of African Americans in the places and at the times of day (i.e., late night hours) when suspicions of contraband carrying is high, we do not know. Some omitted factors from our models may be: 1) geographic shifts in the drug market; 2) concentration of police resources on hot spot areas; 3) other idiosyncratic geographic characteristics such as presence of a college, cemetery, coliseum, major thoroughfares, and so on; and 4) variations in the type of policing areas are subjected to.

Our analysis identifies geographic areas in the city with high rates and some with low rates of both stops and searches of African Americans. Whether the "positive outliers" in the analysis are examples of excessively high rates, indicative of racial bias, is beyond the scope of this report. Neither can we say whether the "negative outliers" are indicative of neglected areas. However, the analysis provides decision makers with information that is useful for purposes of making such decisions.

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Appendix A. Officer Comments at Pedestrian Searches

The following are partial notes from separate pedestrian stop search records of the CMPD:

weapons pat down
SUBJECT WAS VICTIM OF A HOME INVASION.
OBSERVED _________ THE PEDESTRIAN'S …
PEDESTRIAN GAVE CONSENT TO SEARCH HER…
consent was given
consent was given
Known area for robbery of person and bus
subject was sitting in car with drug par
He repeatedly put his hands in his pocket
He had nothing on him at all. Was not
Keys were missing from a stolen car and
The area is known for drug activity. His
contact was very brief, actually lasting
I received information that described the
The information was from a reliable source
R/O OBSERVED SUBJECT INVOLVED IN POSSIBLE
complainant adv a male was in the area
high drug neighborhood
Subject's name is ____ who freq…
Subject was very co-operative.
Marijuana and Paraphernalia located.
Nothing Found Following a short Foot Chase
subject in high drug high crime area
subject was trespassing in a vacant house
subject stated he did not live in area
Investigation for Armed Robberies.
Drug related call for service with details
citizen called in a drug complaint for
subject is known prostitute and drug add
High drug/high crime location. Walked
Manager stated that the subjects in the
Knocked on the door and got consent to search
anonymous drug complaint
The Charlie Drug Enforcement Team received
Officer could smell marijuana
BEING THAT IT WAS A HIGH DRUG AREA AND
DRUG PARAPHNALIA IN THE SUSPECTS ROOM
crack smoke banked down off of ceiling,
Subject was pointed out by a C.I. as an
A consent search was conducted. No weapon
KNOWN DRUG AREA.
Subject was peering around a dumpster
Subject in a high crime/high drug area.
KNOWN DRUG AREA AT 2AM. MALE WALKING IN
AREA KNOWN FOR DRUGS AND PROSTUTION.
KNOWN DRUG AND PROSTUTION AREA.
subject was in known drug location.
ASKED SUSECT IF THERE WERE ANY DRUGS IN
AN ANONYMOUS CALLER STATED THAT THERE WERE
crack pipe found next to subject
Subject made evasive movement upon sight

crack pipe found near subject
the vehicle was parked in an area that
marijuana was confiscated from the vehicle
occupant of a vehicle that was in an are
marijuana was seized from vehicle
trespassing and when they saw police,
INFORMATION WAS OBTAINED THAT THE SUSPEC
call for service gave a description and
Subject standing in cold, by himself, in
Subject sitting in vehicle in high crime
high drug/high crime area. subject was…
HIGH DRUG AREA,
SEARCH RESULTED IN DRUG PARA
caller said the subject was selling coca
subject consented, nothing located. sub
Drug Activity, investigating a citizen
SEARCH_R: Subject was seen behind [address given]
Comp. advised that a suspicious person

Appendix B. Officer Comments at Vehicle Stop Consent Searches

TOLD ME IF I WANTED TO SEARCH HIS VEHICL
SUSPICIOUS ACTIVITY

vehicle was parked in a known location
car was parked in an area known for drug

subject had drug para in his vehicle

DRIVER ACTING SUSPICIOUS, AND CONTINUED
BLUE LIGHT VIOLATION

the driver of the vehicle was driving

NO ID SO I ASKED THE SUBJECT TO SET IN
NO TAG

driver gave consent.

subject seemed nervous and was on a moped

LOOSE STEREO EQUIPMENT AND TOOLS IN PLAIN View
SITTING AT LIGHT

driver movement while in vehicle.
tag year/month was hidden.

Suspicious Movement
No signal

Subject acted suspiciously when asked if
Blue light on front of vehicle.

This officer smelled Marijuana. Asked

observed driver of vehicle in high drug

fictitious tag, driver evasive in answer
vehicle appeared to be trying to avoid

consent search
seatbelt investigation

driver hands shaking and not very sure

OWNERS CONSENT/PC OPEN CONTAINER IN VEHI

smelled marijuana

OFC. [named]THOUGHT HE SAW A FIREARM.

subject was nervous and attempted to get

Subject had philly blounts on passenger

two subjects driving around and making

Subj gave us consent

STRONG ODOR OF MARIJUANA COMING FROM INT

strong odor of marijuana.
expired tag

The suspect was stopped in the middle of
as a matter of routine and officer safety

asked consent for search due to open con

vehicle had the smell of marijuana coming
tag was improperly displayed in rear veh

weapon in vehicle, possible 10-75, drive
suspect looked like dwlr driver

No ID, driving with California tags, Occ

subject was in high drug area, saw him
to confirm it was expired

SUBJ. VOLENTEERED TO BE SEARCHED /HAD VI

Appendix C. Comparisons of Geocoded and Non-Geocoded Stop and Accident Files

TRAFFIC STOPS (Percentages)

	All Cases	Geocoded
CHARACTERISTICS		
African Americans	41.3	42.3
Whites	52.3	51.3
Asians	1.7	1.7
Indians	.1	.1
Unknown	4.6	4.6
Males	65.1	64.9
Females	34.9	35.1
Under 30	43.9	43.9
Number of Cases	94,630	77,125

PEDESTRIAN STOPS (PERCENTAGES)

	All Cases	Geocoded
CHARACTERISTICS		
African Americans	72.2	74.3
Whites	25.4	23.4
Asians	.4	.3
Indians	.2	.2
Unknown	1.9	1.9
Males	85.5	85.6
Females	14.5	14.4
Under 30	48.2	47.2
Number of Cases	6229	5510

ACCIDENTS (DRIVERS ONLY)

	All Cases	Geocoded
CHARACTERISTICS		
African Americans	29.8	30.5
Whites	56.5	55.7
Asians	2.2	2.2
Native Americans	.1	.1
Unknown	.3	.3
Hispanic	9.0	9.2
Other	2.0	2.0
Males	59.3	59.2
Females	40.7	40.8
Number of Cases	61191	51745

Appendix D. Implications of Logging a Dependent Variable

Suppose you have two variables, Y and X. Y is a measure of the amount of policing, such as average number of pedestrians stopped and questioned per week across geographic areas. X is a measure of the average number of calls for service for incivility offenses per week across geographic areas. As X increases by 3 from 5 to 8 to 11 etc. -- as shown below -- Y may increase by a proportion – here 50%. That is, if an area averages 17 calls for incivility offenses, the appropriate number of stops may be 40.5. To represent this relationship between X and Y as a linear one for regression analysis, you take the log of Y, here shown as Z. Notice that Z is approximately increasing by the constant amount of .18. That is, the increase is an additive .18 in Z as one goes up from area to area (8, 12, 18, etc. in Y). Z represents a linearization of the Y variable, a variable that increases proportionately (.50) with each 3 units increase in the number of calls for service. Note that we are not implying here that Y should be related to X as it shown, but that it might be.

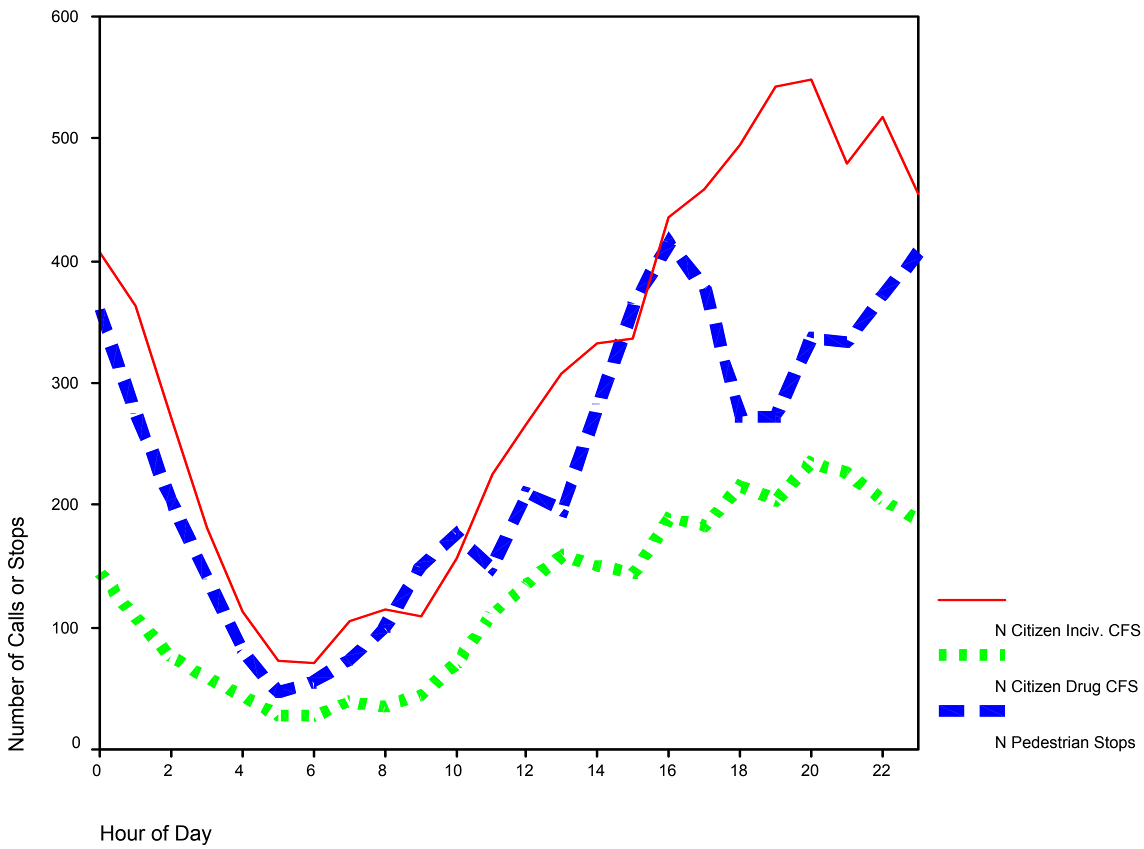
Y	8	12	18	27	40.5
Z	.903	1.079	1.255	1.43	1.607
X	5	8	11	14	17

If Z were entered into a regression equation as a dependent variable, it would have a linear relationship with X, the independent variable in the equation. For every 3 units change in x, z would change by .18. If we substituted Y for Z in the equation, X would not be closely related to Y because the effect of X on Y varies across the values of X (greater effects at the higher X values). By using Z instead of Y in the equation we linearize the relationship between incivility calls and pedestrians stopped per week.

Appendix E. Citizen-Initiated Calls for Service for Incivility Type Offenses

In Figure E.1 below we show the relationship between the hour of the day (all days in 2002) and the number of calls for service that are initiated by citizens and that refer to one of the following incivility offenses: prostitution, drugs, fights, or inebriated pedestrians. Also shown is a line representing the number of citizen-initiated calls for service for drug offenses, as well as a line showing the number of pedestrian stops by the hour of the day. As can be seen, these activities are rather highly correlated. However, there is clearly a large gap in the volume of pedestrian stops in the evening hours (5 pm on to midnight) relative to the volume of calls for service for incivility type calls. In general though, it can be said that there is a strong correspondence of stops and citizen initiated calls-for-service for drugs and other incivility offenses.

Figure E.1 Pedestrian Stops, Calls for Service for Incivility Offenses and for Drug Offenses by Hour of Day



Appendix F. Linear and non-Linear Relationships: Select Graphs with Logged Dependent Variables

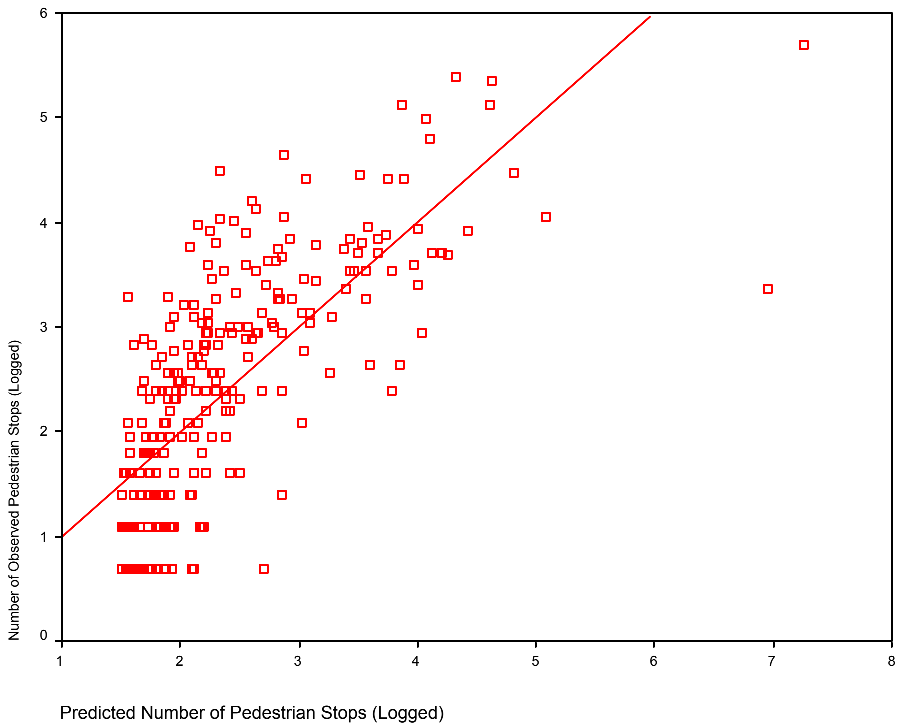
Presumably neighborhoods with many crime problems need more policing, and policing can take the form of stopping pedestrians to question them and ultimately to conduct searches (searches are analyzed elsewhere in the report). To us as researchers, it is an open question whether the number of pedestrian stops, or the number of pedestrian stops of African Americans, should be a linear function of the number of incivility or other crime problems. In general the more reactive one thinks the police should be to specific calls for service, the more the linear additive models, such as those described in the main body of the report, seem the appropriate models for comparisons. The more one thinks that the police should be taking initiatives to "solve problems" in neighborhoods – if only to "crack down" on the problems through stops and searches – the more one would see as desirable a non-linear relationship between calls for service and responses such as stops and searches. That is, in the high need neighborhoods there should be more stops and searches than called for by the linear additive model. A model with a logged dependent variable may be appropriate.

This latter point of view requires some elaboration. Neighborhood dynamics are quite complex. A neighborhood on a "tipping point" of decline may need more policing (including pedestrian stops) than one with a similar crime problem and not on a tipping point. Policing is not only a reactive activity, but also involves crime prevention goals. Stops of pedestrians may be necessary more so in some neighborhoods than others to achieve such goals. Thus, we are reluctant to make any claims about whether the number of African American pedestrian stops is excessive or inappropriate in any particular neighborhood. Our objective here is to document the extent to which the number of African Americans stopped as pedestrians varies independently of the measures that would lead us to expect a given level of such stops. That being the case, we do find several neighborhoods where the number of stops of African Americans as pedestrians is higher than our linear model would indicate to be the expected number of such stops.

In Figure F1 below we show the scatter-plot between the predicted number of pedestrian stops (using the independent variables from the equation represented in Table 5a) and the observed number of stops (both variables represent natural logs). Note that the scatter has a bend or curve, indicating heteroskedasticity, and an explained variance of .524 (below that of .616 reported in Table 5a for the un-logged variable, number of pedestrian stops). These results suggest that the number of pedestrian stops is perhaps better represented by the unlogged count than the logged count represented here. Also compare with Figure One in the text (the un-logged count of the number of African American pedestrian searches). See Appendix D for a discussion of what it means for the analysis to log the dependent variable for a regression analysis.

In Figure F2 below, we show the relationship between the predicted number of vehicular stops and the number of observed vehicular stops from an equation using the variables in Table 18a. Note that the scatter has a bend to it even more accentuated than

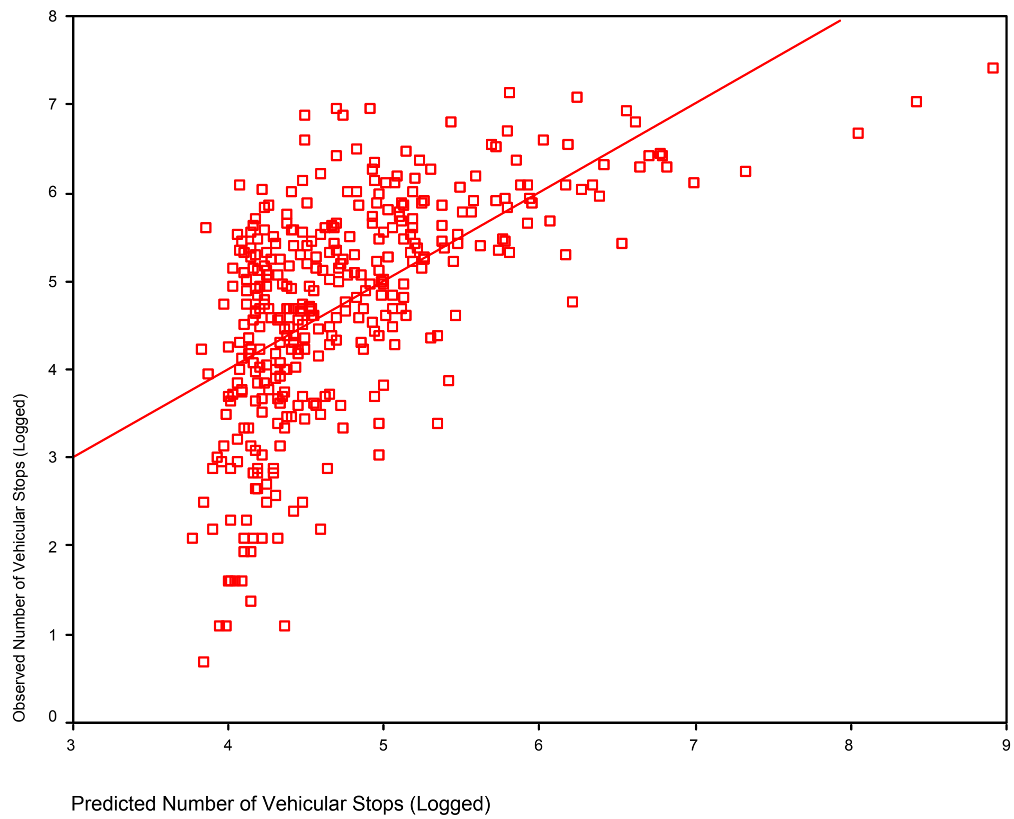
Figure F1. Predicted Number of Pedestrian Stops By Observed Number of Pedestrian Stops in a Block Group, Logged Values, R^2 = .524



the one in F1 above. Also note that the explained variance is 34%, which is less than the explained variance in the un-logged version of this model, 48.5%. This indicates that the un-logged version of the processes of vehicular stops is a preferable model than the logged version – in terms of fitting the observed data.

Towards the goal of assessing whether the linear model or the logged model is a preferable one, we present two additional figures that show the extent to which the number of African American pedestrians stopped in a block group is high or low relative to the model estimates. In Figure 1 in the text we identify the outliers assuming a linear additive relationship between the predicted number and the observed number of African

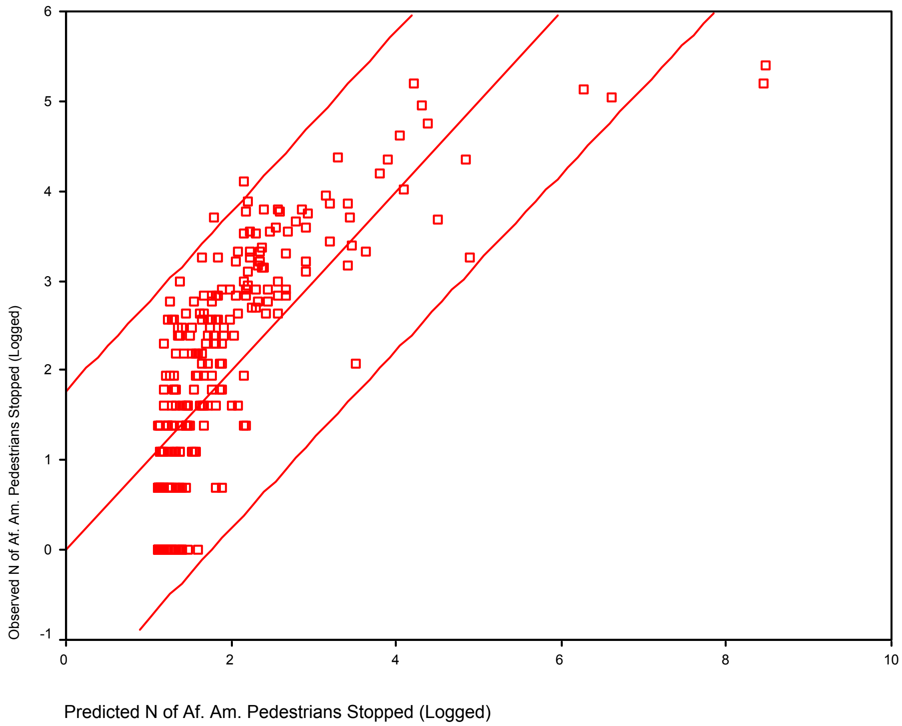
Figure F2. Predicted Number of Vehicular Stops By Observed Number of Vehicular Stops in a Block Group, Logged Values, R^2 = .340



American pedestrian stops. In Figure F3 below, we show the results using the same model as used for Figure 1 but logging the dependent variable. We refer to the latter model as a log-lin model (meaning that the dependent variable has been logged, but the independent variables have not, i.e. they maintain their linear, additive interpretation.)

As we can see in Figure F3, the observations concentrate in an area above the linear regression line, indicating a rather poor fit of the data. Also, the explained variance is only 56.2% compared to approximately 78% in the model for Figure 1 in the text.

Figure F3. Predicted Number of Pedestrian Stops of African Americans By Observed Number of Pedestrian Stops of African Americans in a Block Group, Logged Values, R^2 = .562



Thus it would seem that a linear model (lin-lin) is a better approximation than the logged model (log-lin model). This indicates that police pedestrian searches of African Americans – like police pedestrian searches in general – are better understood in terms of the linear, additive model.

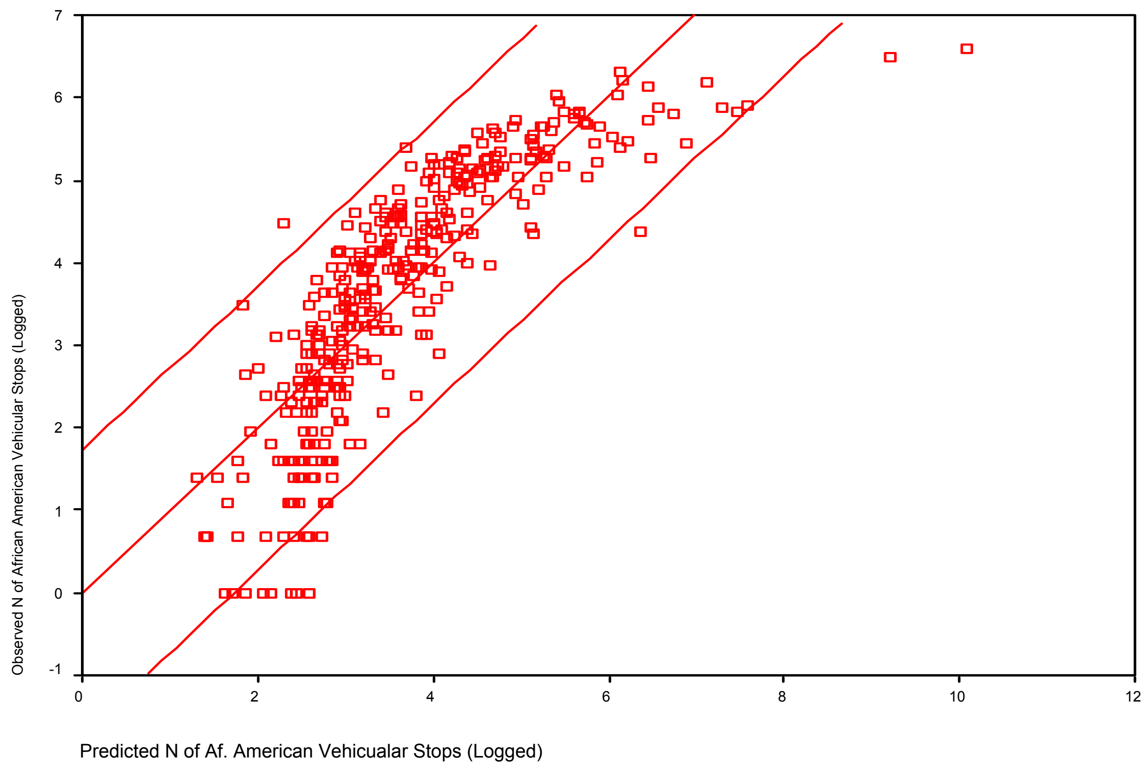
Following the logic discussed above for pedestrian stops, we also developed a model of logged stops of African American drivers. As with the pedestrian analysis, we cannot say that the linear additive model is the most appropriate one. We present an alternative model with the logged dependent variable for comparative purposes. Here, the same independent variables are used, but a transformation of the dependent variable with the natural log transform is included in the regression model instead of the untransformed model. The results are shown in Figure F4.

Here the results show that the use of the logged dependent variable is producing what many researchers would consider a less desirable outcome than did the unlogged variable – rather clearly the values of the residuals of the observed outcomes minus the predicted ones vary as a function of the predicted values. Thus, the graph shows a "sway" or curve pattern in the observations above the regression line and then below as one moves from left to right. This suggests that logging the dependent variable results in a relatively poor fitting model (R^2=.669, considerably less than reported for the un-logged version, .825), and that the process underlying the stopping of African American drivers is perhaps more adequately depicted with the untransformed count in Figure 2 in the main text. The greater "heteroskedasticity" (the technical term for the unevenness in the scatter of predicted values relative to observed values) in the model represented in Figure F4 suggests to us that the linear model may be the better one. That is, the linear model may more directly represent the processes that brings police officers to stop vehicles driven by African Americans.[71]

Note that in Figure F5 we graph the relationship between the predicted number of African Americans consent searched with the observed – where the values are logged. Note that there are more observations above the regression line around the middle of the x axis (number of African American pedestrians consent searches) – a "sway" similar but

[71] Note that in Figure 2 above, there is a slight bend to the scatter of observed values around residual values similar to that seen in Figure 4, but far less pronounced.

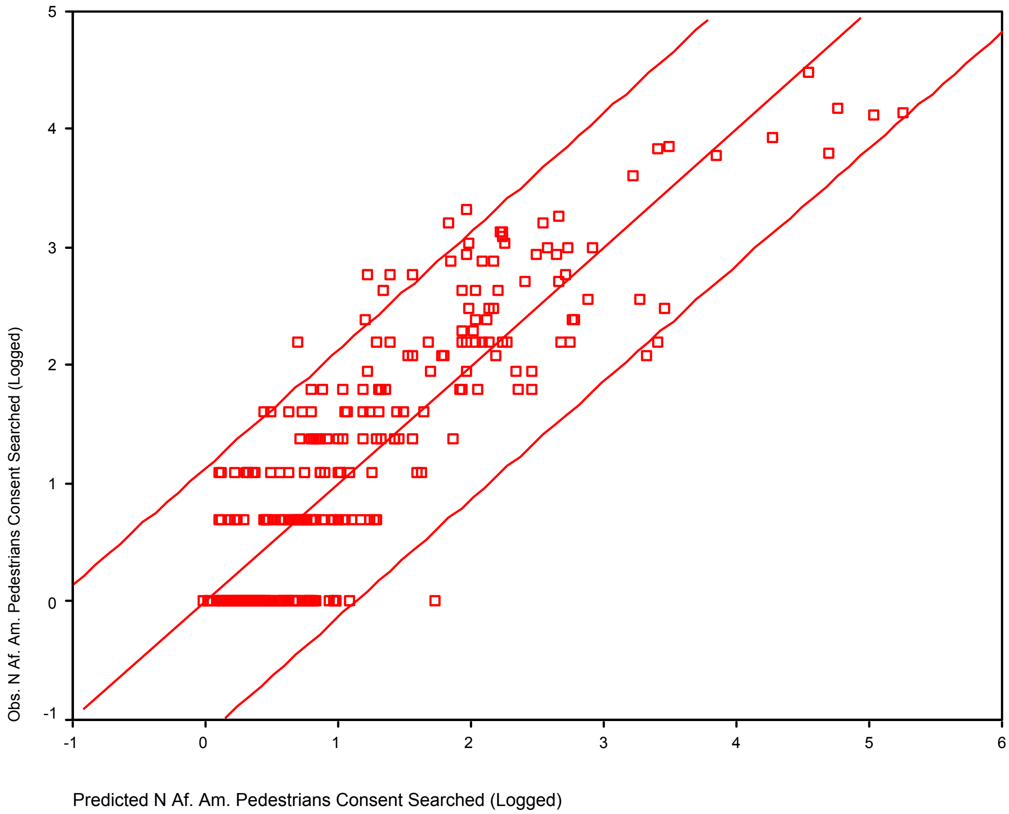
Figure F4. Predicted Number of Stops of Vehicles Driven by an African American by the Observed Number of Stops of Vehicles Driven By African Americans: Logged Results



less pronounced than observed above for pedestrian and vehicular stops. There are also many more positive outliers in this figure than in the figures above that use logged values. Compared to Figure 4 in the text, the scatter of residuals in Figure F5 show a poorer fit (explained variance is at .737, whereas for Figure 4, it is .876).

In Figure F6, the logged number of African American consent searches in the vehicular context are graphed. Results are similar to that observed above for pedestrian searches.

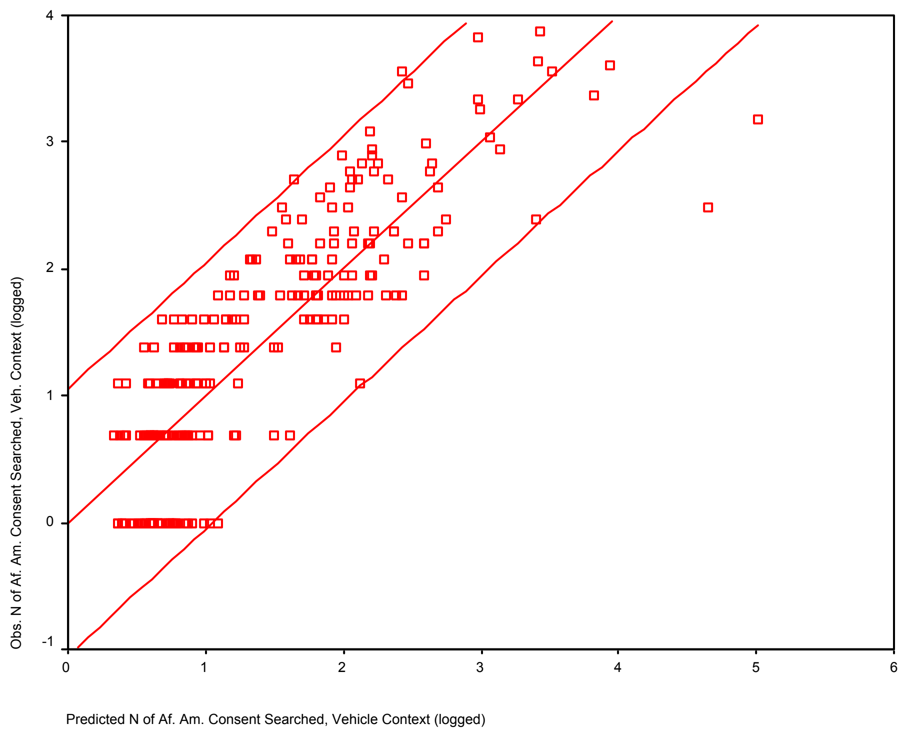
Figure F5. Predicted Number of Pedestrian Consent Searches of African Americans by the Observed Number of Pedestrian Consent Searches of African Americans: Logged Results



In conclusion, the models of the logged dependent variables generally have lower explained variances than the models with the unlogged dependent variables. Also, the scatter of observations in the graphs with the logged variables show a concentration of census block groups above the regression line. These results suggest to us that the relationships among the variables are better modeled using the linear additive model with unlogged dependent variables.

At the same time it should be mentioned that these analyses are somewhat crude relative to possible more sophisticated treatments of the subject. For example, it may be that the relationship between the number of stops and need for them is better modeled making assumptions about "tipping points" such as might be involved in deciding the appropriate degree of policing for hot spot neighborhoods. Perhaps the volume of need must reach a tipping point before disproportionate response is required.

Figure F6. Predicted Number of Consent Searches of African Americans in Vehicular Context by the Observed Number of Consent Searches of African Americans in Vehicular Context: Logged Results



Appendix G. Notes on Use of Regression to Model Number of Stops

The use of regression analysis in the models such as for Table 5a and 5b raises some concerns as to the methods used. Specifically, a forward selection option was used in part to determine what variables would be included in the final models (trimmed models in which non-significant variables have been dropped from consideration. The use of forward selection as a regression procedure option means that the variable with the highest correlation with the dependent variable enters the equation. Then, the variable with the highest partial correlation with the dependent variable, controlling for the variable in the equation is entered. Then, a third variable is selected based on which variable has the highest partial correlation, adjusting for the two variables already in the equation. This procedure continues until all of the independent variables with a statistically significant partial correlation are entered into the equation. Those without a statistically significant coefficient do not enter the equation. After the first variable is entered, other variables on the list of variables that could be entered into the model are somewhat "disadvantaged" to the extent that they are correlated with the variable already in the equation. Those not yet in the equation (variables enter one at a time) must have a statistically significant partial correlation with the dependent variable net of the effect of variables already in the equation. Thus a variable with a reasonably high correlation with the dependent variable may not enter the equation if it is correlated even only modestly with variables in the equation. In essence, the forward selection procedure is essentially one that gives the strongest variable the opportunity to limit what other variables can enter the model. For example, in the Table 5a, the number of incivility offenses reported by citizens in 911 calls is the strongest predictor of the dependent variable (number of pedestrian stops). (Recall that we omit a variable with a higher correlation .82 -- number of successful pedestrian consent searches -- from the list of potential predictors). The number of incivility offenses is also highly correlated with number of violent offenses (.77) and moderately correlated with number of breaking and entering offense calls for service (.59). Because of these correlations with the variable already in the equation, both of these variables would have to have variation "unique" to it in sufficient degree to have a statistically significant partial correlation with the dependent variable when controlling for number of incivility calls for service. All else equal, the higher the correlation with the variable in the equation, the less likely an "unentered" variable will be able to enter the equation – sort of a "survival of the fittest" process. This aspect of the "forward entry" of variables into the regression equation explains why there is the combination of many strong correlations in Table 4 with the dependent variable (number of pedestrian stops) yet so few statistically significant variables in the model of Table 5a.

We are sensitive to the limitations discussed above regarding forward entry regression strategies. For the model in Table 5a, for example, we tested a model with the variable number of incivility calls for service omitted. The variable "number of assaults" became the most important predictor of number of pedestrian stops. Still, neither the racial composition of the populace nor of drivers was statistically significant. Population, number of hit and run, and number of breaking and entering calls for service were the other variables in the model that were statistically significant. We then omitted the variable number of assaults and re-estimated the model. Number of robbery calls for service now becomes statistically significant, along with number of violent offense calls for service. Population size and number of hit and run remain statistically significant in the model, as they were in the previous model. In yet another model, we omit number of robberies. We found that the other variables maintain their status as statistically significant variables in the model, while no new variables enter the equation (because they fail the entry criterion of being statistically significant). Again, the race measures (African Americans in residency or in accidents) are not statistically significant.

We interpret the findings across all of these models to mean that the forward selection procedure does not lead to an arbitrary or misleading finding as to the relative unimportance of racial composition in determining the number of pedestrian stops in these data. It would seem that the findings that we present in Tables 5a and 5b are robust to the questions about the use of forward entry procedures.

Appendix H. Alternate Models of Number of African American Stops

On another methodological matter -- the use of the variable number of successful pedestrian consent searches as a predictor variable of number of pedestrian stops (see Table 5b) -- we argue that if we had a measure such as the number of successful pedestrian consent searches (drugs or alcohol found) in a census block group in 2001, that it would be highly correlated with the number of successful pedestrian consent searches in 2002. If we used such a measure, we could not be criticized for there being a partially "necessary" correlation between search success and number of stops. Presumably police stop pedestrians (often for the purpose of finding drugs) in areas where drugs are known to be distributed and where they have had past success in finding those drugs on the pedestrians that they search. We think it is important to have a measure of search success in the equation. Note that in an earlier draft of this report we tested an alternate measure, whether drugs were mentioned in the open-ended comments recorded by the officer when a stop was made. We also found that variable to be highly correlated with the number of pedestrian stops and to be a statistically significant predictor in the regression equation.

The important consequence to using the variable number of successful pedestrian consent searches is in the stage of the research in which we define positive and negative outliers. Some census block group areas might be defined as a positive or negative depending on whether the successful search variable is in the equation or not.

Because there is some concern about the inclusion of the variable number of successful consent searches in a model of the number of African American pedestrian stops, we also present a model and the outliers from the model for an alternative model without the successful search variable. Table H1 below shows the results of the alternative model of the number of pedestrian stops of African Americans. Note that the explained variance is 61.1, considerably less than the 80.5% reported in Table 9 (which includes the effect of number of successful pedestrian consent searches). As can be seen here, when we omit the number of successful pedestrian consent searches as a variable, other variables enter into the equation in its stead. The predicted values of this equation are plotted against the observed values, and are shown in Figure H1 below.

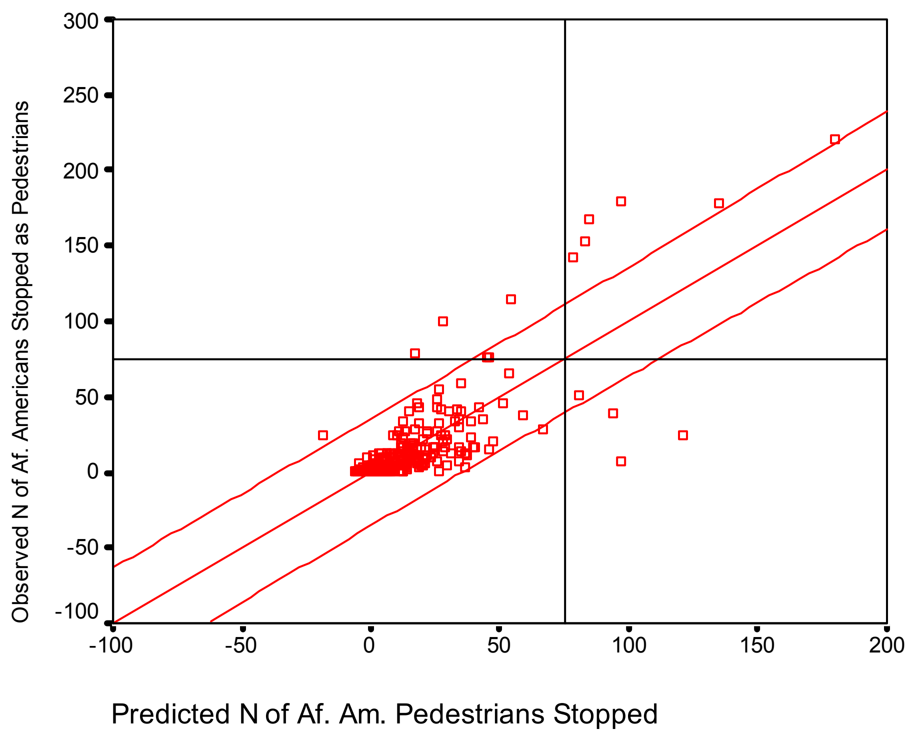
In Figure H1 we see that there is a somewhat different pattern of outliers than we observed in Figure 1 in the main text. There are about 10 positive outliers scattered above the upper line of the 95% confidence interval and only four negative outliers (below the lower 95% confidence interval) and they are all among the higher predicted values of the model. This pattern of outliers suggests to us that it is important to include a measure of the success of stops and the often resulting searches that occur as the pattern is less bimodal (two-pronged) in Figure 1 than in Figure H1.

At the same time, Figure H1 suggests to us that the results are different from those in Figure 1, yet they are not so different so as to suggest that one would come to largely different conclusions using the model in Table H1 as in Table 9 in the text. That is, the omission of the success variable, while making a difference, would not lead to a radically different identification of positive or negative outliers. Nevertheless, it should be noted that some of the census block groups that are positive outliers in Figure H1 are not in Figure 1 in the main text.

Table H1. Alternate Model of Number of African American Pedestrian Stopped, Omitting the Variable Measuring Number of Successful Pedestrian Consent Searches

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.	Collinearity Statistics	
R^2 = 61.1%	B	Std. Error	Beta			Tolerance	VIF
(Constant)	-3.888	2.738		-1.420	.157		
# of Incivility Calls for Service	.649	.053	.751	12.239	.000	.374	2.671
# Whites Stopped as Pedestrians	.690	.176	.193	3.924	.000	.585	1.709
# Assault Calls for Service	2.008	1.017	.094	1.974	.049	.628	1.593
#Violent Offense Calls for Service	-.235	.074	-.227	-3.165	.002	.275	3.643
# of Af. Am. Residents	.008	.003	.163	2.537	.012	.342	2.926
# of Residents Ages 18-29	-.012	.004	-.157	-3.038	.003	.527	1.898

Figure H1. Alternate Model Results of Outliers: Number of African American Pedestrian Stops



Appendix I. Spatial Heterogeneity

Large units of analysis can result in a lack of precision in the measurement of attributes of the large areas such that the magnitude of the correlations across large areas may be attenuated. Suppose there were two large districts in which the percent African American was 50% and percent white was 50%. Suppose further that in Area One all of the whites lived adjacent to one another on the north side of the district and all the African Americans lived adjacent to one another on the south side of the district. In the other area, Area Two, blacks and whites were intermixed such that one's next door neighbor was equally likely to be white or black. Both areas would be rated as equally integrated by the 50% measure, but due to the greater heterogeneity in Area One, the "segregated" area ("heterogeneity" relative to the presumption that the entire district is racially intermixed), the social dynamics of that area could be drastically different than in the truly integrated district, Area Two. If these two large areas were to be divided into smaller areas, Area One could more accurately reflect the heterogeneity within the area because half of the sub-districts would be 100% African American (south side) and half 100% white (north side). The subareas of Area Two would have values of 50%, as before. Now, however, using the smaller units of analysis, all else being equal, the correlations between percent African American and other attributes of a community that might be race-related (e.g, income, education) would have higher values due to the more accurate measurement when smaller units of analysis are used.

Take another example of the possible consequences of spatial heterogeneity, one more closely associated with the issues studied here. In a large unit, such as a police district, a measure of citizen presence, such as the proportion of the residents who are African American could more easily have a low correlation with the proportion of drivers stopped who are African American because of the "heterogeneity" within the district of where African Americans drive relative to where police patrol. For example, if a large highway that serves as a commuter thoroughfare ran through a mostly African American community, and mostly whites drove on that thoroughfare (because the thoroughfare connected a white "bedroom community" with the downtown business area), then there could be a low correspondence between African American drivers in accidents and in residency within that area (assuming the police monitored all the roads in the district equally and there were more accidents on the busy highway because of high density rush hour traffic, i.e., probably not preventable with more police patrolling). Such measurement errors across districts could in part account for a low correlation between the proportion African American residents and the proportion African Americans involved in vehicular stops.

To help minimize the attenuation of correlations across districts, we use smaller geographic areas than the 12 police districts of the CMPD. This allows us to study 25 census block groups rather than one district, and better isolate the thoroughfare effect in the 6 census block groups, for example. There will thus be a high correspondence presumably between the proportion of residents who are African American and who are stopped in most of the areas (19 of the 25) such that the correlation between proportion of residents who are African American and proportion stopped who are African American should be improved relative to correlations across the 12 districts – although there still would be a "mismatch" in the 6 census block groups.