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THE DALLAS AVL EXPERIMENT: EVALUATING THE USE OF AUTOMATED VEHICLE LOCATOR TECHNOLOGIES IN POLICING

Final Report

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The Police Foundation is a national, nonpartisan, nonprofit organization dedicated to supporting innovation and improvement in policing. Established in 1970, the foundation has conducted seminal research in police behavior, policy, and procedure, and works to transfer to local agencies the best information about practices for dealing effectively with a range of important police operational and administrative concerns. Motivating all of the foundation's efforts is the goal of efficient, humane policing that operates within the framework of democratic principles and the highest ideals of the nation.

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ABSTRACT

Law enforcement agencies lack specific information describing where police officers patrol when not responding to calls for service. Instead they have snapshots of events that are handled by police such as the locations of crime reports, arrests, traffic citations, and pedestrian stops. While computerized crime mapping has enabled "smart policing" and police have become more scientific in the ways in which they respond to crime (Bureau of Justice Assistance, 2010; Robinson, 2011), police agencies still have little ability to assess the effectiveness of their deployment strategies in relationship to their goals.

Our study sought to examine these two key gaps in the advancement of recent police innovations. If the police have knowledge about where patrol resources are concentrated in a police agency, can police Commanders more successfully manage broad patrol resources? Within the context of a Compstat model, can they ensure that crime hot spots gain increased levels of patrol? Finally, if such knowledge were available to the police will that help them to prevent crime? We think that the answers to these questions are key to the advancement of policing. Our study is the first we know of to test these questions directly.

Since the early 1990s, hot spots policing has emerged as an important policing strategy. Sherman and Weisburd (1995) coined the term and argued that the police should not water down the dosage of police patrol across entire beats, but should focus it upon the specific places where crime was concentrated. While police scholars now agree widely that preventive patrol over larger areas is not effective (Weisburd & Eck, 2004; Bayley, 1994), the introduction of automated vehicle locator (AVL) technology allowed us to see whether provision of detailed information on actual patrol dosage to police managers would allow for more effective

allocation of patrol in beats and following this significant reductions in crime. We were also able to examine these questions for crime hot spots identified during Compstat meetings.

We used a blocked randomized experimental design to examine these questions. First, we used trajectory analysis to identify four groups of beats with similar crime trajectories. Each of the beats within a trajectory group was randomly allocated to treatment or control. Commanders received information on the measured deployment levels (the amount of hours of vehicle presence as measured by an Automated Vehicle Locator (AVL) system) received by the treatment beats but not the control beats. In addition, they received AVL measured deployment information about Compstat hot spots (those identified for specific deployment strategies) in the treatment areas but not in the control areas.

At the beat level, access to AVL measured deployment information led Commanders to request significantly higher amounts of patrol presence but did not result in an increase in actual patrol levels. At the hot spot level, it is important to note that our unit of analysis is no longer the same as our randomization unit. Thus, we interpret these results with caution. At the hot spot level, AVL does not lead Commanders to request higher levels of patrol, but it did lead to higher actual levels of patrol at those places. Also, in contrast to the beat level findings, we find treatment hot spots have about a 20 percent relative “decline” in crime.

The Dallas (Texas) AVL Experiment provides important information to improve our understanding of how AVL technologies can be used to maximize patrol in police agencies. Our data suggest that, at least in cities like Dallas with large geographies, AVL information will not aid patrol allocations in large geographic areas because patrol coverage in beats is largely a function of cross district dispatch rather than Commander-specified deployment. However, it is effective in achieving higher levels of patrol in hot spots and significant reductions in crime. Additional studies are needed in other cities and focusing on hot spot areas to better understand the potential value in using AVL for deployment.

TABLE OF CONTENTS

Abstract.......... iii

Executive Summary.......... ix

Research Questions.......... x

Research Design.......... xi

Study Units of Analysis: Beats and Hot Spots.......... xi

Measuring Intended and Beat Level Deployment.......... xii

Total Crime.......... xii

Creating Experimental Blocks Using Trajectory Analysis of Total Crime.......... xiii

Random Assignment of Beats.......... xiv

Treatment: Feedback on Deployment Levels Achieved.......... xv

Control Condition.......... xv

Findings.......... xv

Conclusions and Implications for Practice.......... xviii

Acknowledgements.......... xx

Purpose of the Study.......... 1

The Potential for Using AVL Technology to Identify Where Police are Deployed.......... 4

Can Police Patrol Impact Crime?.......... 7

Research Questions:.......... 13

Experimental Design.......... 16

The Study Site And Experimental Period.......... 16

Study Units of Analysis: Beats and Hot Spots.......... 20

Quantifying Police Presence Using Intended Deployment.......... 23

Measuring Beat Level Deployment.......... 23

Measuring Hot Spot Level Deployment 24
Quantifying Actual Police Presence Using AVL Measured Deployment 27
Total Crime 28
Creating Experimental Blocks Using Trajectory Analysis of Total Crime 29
Random Assignment of Beats 34
Statistical Power 35
Treatment: Feedback on Deployment Levels Achieved 36
Treatment Provided For Beats 36
Treatment Provided to Compstat Hotspots 39
Control Condition 42
Findings 42
The Effects of AVL Knowledge on Beat Area Outcomes 43
The Effects of AVL Knowledge on Hot Spots Policing 54
Discussion 62
Limitations 67
Conclusions 68
References 70
Dissemination of Research Findings 75
Appendix A: Trajectory Analysis Model Selection and Diagnostic Statistics 76
Appendix B: Data collection and Reporting 79
Background Information 79
Project Reports 79
Organizational Strategy 82
The Reporting Process 83

Appendix C: Additional tables 89

About the Authors.. 103

EXECUTIVE SUMMARY

Law enforcement agencies do not typically have a comprehensive data source to measure where police officers spend their time on patrol. Like individual frames from a full length movie, locations of calls for service, crime incidents and arrests provide snapshots of where police conduct those activities, but the more numerous missing frames represent important gaps. This means police agencies have little ability to assess the effectiveness of their deployment strategies in relationship to their goals. In contrast, computerized crime mapping has allowed the police to become more scientific in the ways in which they respond to crime. "Smart policing" has become an everyday buzz word for police as they have become able to track crime carefully almost in real time (Bureau of Justice Assistance, 2010; Robinson, 2011).

Our study sought to examine these two key gaps in the advancement of recent police innovations. If the police have knowledge about where patrol resources are concentrated in a police agency, can police Commanders more successfully manage broad patrol resources? Within the context of a Compstat model, can they ensure that crime hot spots gain increased levels of patrol? Finally, if such knowledge were available to the police will that help them to prevent crime? We think that the answers to these questions are key to the advancement of policing. Our study is the first we know of to test these questions directly.

Since the early 1990s, hot spots policing has emerged as an important policing strategy. Sherman and Weisburd (1995) coined the term and argued that the police should not water down the dosage of police patrol across entire beats, but should focus it upon the specific places where crime was concentrated. While police scholars now agree widely that preventive patrol over larger areas is not effective (Weisburd & Eck, 2004; Bayley, 1994), the introduction of AVL technology allowed us to see whether provision to police managers of detailed information on actual patrol dosage would allow for more effective allocation of patrol in beats and following this significant impacts on crime. We were also able to examine these questions for crime hot spots identified during Compstat meetings.

RESEARCH QUESTIONS

Our study sought to increase knowledge in the two key research areas identified above and led us to ask eight specific research questions (four at the level of police beats and four at the level of hot spots):

1. Does knowledge about actual police patrol time influence the time that police managers expect patrol cars to spend in patrol beats under their supervision?
2. Does knowledge about actual police patrol influence the amount of patrol delivered in a beat area?
3. Does knowledge about actual police patrol allow managers to gain greater consistency between the amounts of patrol that they request in any police beat with the actual amount of patrol delivered?
4. Does knowledge about actual police patrol lead to crime reductions in the experimental beats?
5. Does knowledge about actual police patrol influence the time that police managers expect patrol cars to spend in directed patrol areas in their beats?
6. Does knowledge about actual police patrol influence the amount of actual patrol delivered in a hot spot area?
7. Does knowledge about actual police patrol allow managers to gain greater consistency between the amount of patrol that they request in any directed patrol area and the actual amount of patrol delivered?
8. Does knowledge about actual police patrol at hot spots lead to crime reductions in the directed patrol areas in the experimental beats as contrasted with the control beats?

Research Design

We designed the experiment in collaboration with the Dallas (Texas) Police Department (DPD). The DPD has been using AVL technology since 2000 and has AVL installed in virtually all patrol cars, currently 873 vehicles. Ample time has elapsed to address various issues including possible obstruction by officers of AVL technology and officer/union resistance based on AVL technology being a possible threat to their personal freedoms on the job due to its ability to capture and monitor GPS data.

Study Units of Analysis: Beats and Hot Spots

A marked benefit of the DPD as our experimental site is that the department has fully implemented Compstat with routine meetings for assessing crime problems. Compstat provides a management strategy to hold division Commanders accountable for deployment and crime control in their respective districts. In addition, DPD has a "directed patrol" philosophy where it is the responsibility of division Commanders to actively manipulate patrol to meet emerging problems and this process is reviewed weekly. The underpinning of this philosophy includes the conceptual idea that a car or an "element" should be available to service each beat at all times so as to provide efficient response time to calls for service. Beats are the operational unit for deployment decisions and thus were chosen as the units of analysis in the experiment. Hot spot areas identified during Compstat meetings as candidates to receive directed patrol were the units of analysis in the study of hot spots.

Measuring Intended and Beat Level Deployment

A key issue in our study is the impact of AVL on expectations regarding the deployment of patrol resources. Accordingly, we needed to develop mechanisms for collecting data on how much time police Commanders expected patrol officers to spend in specific areas. Following our research questions, we measured intended deployment at two levels of analysis, beat, and hot spot. We collected beat level intended deployment through a web-based internet application that administrative sergeants filled in daily. Intended deployment in hot spot areas was measured via a form that was filled in at the weekly divisional Compstat meetings. DPD personnel running the meeting catalogued each hot spot area identified and specific amounts of increased attention requested for those places.

Actual deployment achieved was measured via AVL data. These data include latitude/longitude position, speed of the vehicle, and a unique vehicle identification number. When vehicles are stationary, a data point is created every 15 seconds. As a vehicle begins to move, a data point is created for every 300 meters that the vehicle travels. The DPD wrote a program which aggregates time spent by police officers in quarter mile (1,320 foot) square grid cells that covered the city. Department personnel ran this program and supplied the research team with aggregated time spent in beat and each grid cell. AVL measured patrol constituted our primary measure of police patrol presence. It is important to note that the measure captures all police presence in a beat (not just that of the officers assigned to a beat).

Total Crime

Total crime included all homicide, rape, robbery, aggravated assault, burglary, theft, unauthorized use of motor vehicle (UUMV), auto theft burglary of motor vehicle (BMV), narcotics/drugs, vandalism/criminal mischief, and assault. To account for cases of property crime for which an exact time of occurrence was unknown, we conducted an aoristic analysis of the total crime data.[1] We used total crime data for 2009 as the basis for establishing the blocking scheme and total crime as an outcome measure in the evaluation of whether the information provided by AVL regarding patrol deployment achieved would reduce crime.

Creating Experimental Blocks Using Trajectory Analysis of Total Crime

Our initial analysis of crime data in Dallas showed that crime rates varied a good deal between the beats. Such large variation in the baseline for a key indicator, that was also strongly correlated to patrol allocations, led us to use a block randomized design for our study (Gill & Weisburd, In Press; Weisburd & Gill, In Progress; Weisburd & Taxman, 2000). Block randomized designs allow a researcher to increase confidence in the equivalence of study groups in an experiment by first defining broad categories of cases and then randomizing units within those categories. For example, in our case if we could identify beats with similar crime trends, we could equally allocate beats randomly in groups that reflected similar trajectories of crime over time. This approach also has the benefit of increasing the statistical power of a study (Gill & Weisburd, In Press; Weisburd & Gill, In Progress).

We relied upon group-based trajectory analysis (Nagin, 1999; Nagin & Land, 1993; Nagin & Tremblay, 2005) as a technique for identifying broad groupings of beats for randomization in

[1] Aoristic analysis involves spreading the crime risk equally across the hours of the timespan by assigning each hour a portion of the probability the crime occurred in that time period (for more details see Ratcliffe, 2000, 2002).

our study. Formally, the model specifies that the population examined is comprised of a finite number of groups of individuals who follow distinctive developmental trajectories. Each group is allowed to have its own offending trajectory (essentially a chart of offending rates throughout the time period) described by a distinct set of parameters that are permitted to vary freely across groups.

We identified four different developmental groups at beats in 2009. One group represents beats which have very low weekly crime levels. This very low crime group has 21 beats (9.1%) and its members experienced roughly three to six crimes per week. The 94 low crime beats (40.5%) ranged from a low of six to a high of nine crimes per week. The medium crime group contains the largest number of beats (n = 100, 43.1%) and ranges from 9.5 to just over 13 crimes per week. Seventeen beats (7.3%) were significantly higher than the medium crime group ranging from 15 to 25 crimes per week. The gap of two crimes per week separating the medium and high crime groups is the largest among any of the groups.

Random Assignment of Beats

The 232 beats were allocated equally to two groups using the pseudo-random number generator in Excel. The distribution was conducted in four statistical blocks, based on the results of the trajectory analysis. One group of beats was the treatment group (N=116) and the other the control group (N=116). Police managers received information about the actual patrol levels received in the previous week to use in their deployment decisions for the treatment beats Police managers did not receive information about police presence as measured by AVL for the control beats. Police managers were briefed on the design of the study and asked to report their daily staffing allocations to beats for both treatment and control areas. Patrol officers were not informed of the study.

Treatment: Feedback on Deployment Levels Achieved

After a series of meetings with Dallas Police Department field Commanders, we created two feedback forms which were given to the DPD Division Commanders on a weekly basis. Both forms contained information about AVL measured deployment, one for beats and the other for Compstat hot spot areas.

Control Condition

The control condition consisted of standard police responses in the beats that were allocated as controls. Accordingly, police continued to patrol these areas at the normal levels and would respond to calls for service originating in these areas as usual.

Findings

Our findings regarding the influence of AVL knowledge on allocations of police patrol, and its impacts on crime are intriguing. We find that, overall, AVL knowledge led Compstat Commanders in Dallas to increase the amount of patrol that they expected in their beats as compared to control beats. But that increase in expectations did not lead to a significant increase in the actual allocation of patrol. Not surprisingly, we did not find any crime prevention benefits at the beat level for the treatment condition. This would imply that AVL knowledge, at least in the way that it was applied in Dallas, does not lead to any greater consistency between expectations and patrol achieved.

When we examine hot spots, we find precisely the opposite impact of AVL. It did not affect the overall number of hours assigned as compared to control beats, though it did increase the amount of patrol actually performed (despite the larger number of hot spots assigned) in the treatment condition. This increase in patrol appears to have led to a decrease in crime in the treatment hot spots.

How can we explain these markedly different results found at different geographic levels of policing? And what insights do our findings bring to the use of AVL in the future in police agencies? This is what we focus on in the following discussion of our findings. We think they make very good sense given what we know about policing today and despite the limitations of our study (to be discussed before concluding) our findings lead to strong policy conclusions.

Why does AVL increase expectations of patrol in the beat level, but not have any observed impact on the amount of patrol performed? We think it likely that the increase in expected patrol is a result of police Commanders observing how much patrol they get in each beat relative to the broad assignments that they believe they are making regarding police resources. In Dallas, as in many other cities, the Commanders assign a specific number of cars to each police beat each week. But in reality, the number of hours of patrol that is actually delivered to those beats will be determined by factors that are not under the control of Commanders. For example, in Dallas cross beat dispatch is common when the burden of calls for service to the police grows. Despite officers being assigned to a specific beat, they are likely to be sent across beats when call dispatchers need to assign an emergency call. In geographically large cities such as Dallas, the time it takes to answer calls on the other side of the city or even just outside the assigned beat is considerable.

With access to the actual patrol figures, the AVL beat Commanders clearly felt that the number of hours of patrol performed was not high enough. We suspect that having seen the actual deployment figures they wanted to increase the number of hours overall spent in particular beats under their command. AVL information gave the Commanders the sense that they might have more control over patrol resources. But the reality was that the patrol resources of the department, as in many other departments, was being driven more by the emergency dispatch system than by the dictates of the Commanders (Famega et al., 2005; Reiss, 1992).

But this raises the question of why Commanders could bring greater resources to crime hot spots. Moreover, why did the Commanders not expect more hours at treatment hot spots than control hot spots if they expected more resources at treatment beats but not control beats? The answer to this latter question can be found perhaps in the more specific nature of hot spots policing allocations. Beat areas are large geographies, and specifying how much patrol should be given to each is difficult to focus upon in very specific terms. Of course, high crime beats would be assigned more patrol than low crime beats. But the boundaries of such assignment numbers would be expected to be imprecise. However, police attention to specific places, or hot spots, is a much more concrete focus for Commanders, and we suspect that in coming to a decision about how much patrol to allocate they have clear expectations that are not likely to be influenced simply by a desire to gain more patrol. The treatment for any specific hot spot is in this sense independent of knowledge about police patrol brought by AVL data.

This indeed fits the logic as we noted earlier for hot spots policing more generally. One of the major findings of the Minneapolis Hot Spots Patrol Experiment (Sherman & Weisburd,

1995) was that police could be effective in reducing crime if they focused their resources on crime hot spots. Sherman and Weisburd argued that it was wasteful to spread preventive patrol across a city if crime was concentrated at a small number of places. Moreover, focusing police resources on specific places would allow the police to bring higher dosages of patrol to those places (Weisburd, 2008; Weisburd & Telep, 2010). This experiment shows that AVL information allows Commanders to increase the concentration of ordinary patrol resources at crime hot spots.

What is new here is that the introduction of AVL can help the police to more efficiently and effectively increase police patrol at crime hot spots. This is an important finding, especially in an era when it is unlikely that police resources will be increased. Our study suggests that with existing resources the use of AVL can increase patrol time at hot spots and through such increases in patrol reduce crime.

Conclusions and Implications for Practice

The Dallas AVL Experiment provides important new data for our understanding of how AVL technologies can be used to maximize patrol in police agencies. Our data suggest that, at least in cities like Dallas with large geographies, AVL information will not aid patrol allocations in larger geographic areas. Indeed, we find that the introduction of AVL as a management tool might be expected to lead to frustration in management in such police agencies. In our study AVL led to increased expectations for patrol at the beat level, but no significant differences in actual patrol levels. We do not assume that the latter finding is due to intentional efforts on the part of patrol officers to ignore the dictates of Commanders, but rather reflects the limited control that police Commanders have over patrol resources once emergency response systems, especially cross district dispatch approaches, are factored into the patrol equation. This finding suggests that AVL might lead to increased friction between Commanders and the patrol force, as expectations are inflated by AVL knowledge, but patrol allocations do not increase. Not surprisingly, our study shows no significant impact of AVL knowledge on beat level crime rates.

Despite the sobering findings in our study regarding the use of AVL as a beat level management tool, our study suggests that AVL knowledge is a promising tool for enhancing hot spots policing approaches. Expectations for patrol hours in hot spots were not affected by the experimental conditions. However, AVL information did lead to significantly higher hours of patrol at the hot spots identified. AVL in this context can be an effective tool for enhancing hot spots policing approaches. Moreover, this increased patrol at hot spots was found to lead to lower levels of crime in the treatment areas.

These findings overall provide important guidance for police agencies. On one hand they should be cautious in employing AVL as a management tool for large area patrol deployment. On the other, AVL can be an effective tool for enhancing hot spots policing approaches. Given the very strong empirical findings of the effectiveness of hot spots policing (Braga, 2007; Braga & Bond, 2008; National Research Council [NRC], 2004; Sherman & Weisburd, 1995; Sherman & Rogan, 1995; Weisburd & Green, 1995; Weisburd et al., 2006) and the findings of this study, our study suggests wider use of AVL in bringing directed patrol to hot spots areas.

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Purpose of the Study

Currently police agencies have little ability to assess the effectiveness of their deployment strategies in relationship to their goals. Police agencies use calls for service, crime incidents, and arrests as indicators of both crime and police activity. In the case of identifying crime, these data combined with computerized crime mapping now allow police agencies to know exactly where crimes occur in their cities, and at what times. Such information has allowed the police to become more scientific in the ways in which they respond to crime. "Smart policing" has become an everyday buzz word for police as they have become able to track crime carefully almost in real time (Bureau of Justice Assistance, 2010; Robinson, 2011). But despite advances in our knowledge about where crime is, the police know little about where "the police are." Calls for service which track police responses to specific incidents capture only specific moments in time within an officer's daily routine and offer limited knowledge as to where officers are located during a large portion of their shifts.

This lack of information on where officers are when not responding to calls for service or crime hampers efforts to implement two of the most promising policing innovations, Compstat and hot spots policing. One of the tenets of Compstat is being able to more effectively deploy police resources (Bratton & Malinowski, 2008; Weisburd, et al., 2003; Weisburd et al., 2001; Willis, Mastrofski, & Weisburd, 2007). But a program like Compstat cannot be fully implemented in police agencies if the agencies cannot monitor carefully the allocation of the largest proportion of police resources—police patrol. "Hot spots" policing relies on identifying problem areas and then deploying additional resources to those areas (Braga &Weisburd, 2010; NRC, 2004; Weisburd & Braga, 2006). Most hot spots policing programs have relied upon special units under specific command control (see e.g., Hope, 1994; Lum et al., 2010; Weisburd et al., 2006) or have relied upon researchers to track the amount of police presence in specific locations (e.g. Braga & Bond, 2008; Sherman & Rogan, 1995; Sherman & Weisburd, 1995). But if hot spots policing is to become an ordinary part of the patrol effort in police agencies, Commanders must be able to track and monitor whether patrol resources are actually being brought to hot spots.

Our study sought to examine these two key gaps in the advancement of recent police innovations. If the police have knowledge about where patrol resources are concentrated in a police agency, can police Commanders more successfully manage broad patrol resources? Within the context of a Compstat model, can they ensure that crime hot spots gain increased levels of patrol? Finally, if such knowledge were available to the police will that help them to prevent crime? We think that answers to these questions are key to the advancement of policing. Our study is the first, of which we are aware, to test these questions directly.

In theory, the police have been able to track the location of police vehicles for many years. As early as the 1980s, police agencies in the U.S. began to introduce Automated Vehicle Locator (AVL) systems. These systems provide geographic information from vehicles to a central data source, something that we are all familiar with in terms of using GPS in our cars. But while in practice the police have had knowledge about the geographic positions of their cars in many agencies for a number of years, the development of systems to systematically organize this information has lagged behind the technology for locating cars. And in some sense the police did not adopt such technologies to track where the police patrol but rather as a safety feature to be able to locate cars in emergencies (Federal Highway Administration, 1997; Larson, Colton,

& Larson, 1976; Strandberg, 1993). Moreover, in most police agencies not all police cars were equipped with AVL, and this meant that the agencies would have only partial coverage even if they sought to use AVL as a management tool. Added to this have been objections by many police officers and unions to the use of AVL to track officers in the field (Manning, 1992a, 1992b; Sorensen, 1998). What this has meant is that despite the technological possibilities for AVL in police management, police agencies generally have not been able to use AVL as a management tool for deployment.

Our study provided an opportunity to bring scientific knowledge to whether AVL actually would improve the ability of police managers to allocate police officers in the field, and through such allocations reduce crime. We capitalized on the fact that the Dallas Police Department (DPD) had introduced AVL technology in almost all of its patrol vehicles (n = 873) by 2000. Moreover, the DPD was interested in knowing whether its extensive AVL coverage could be capitalized upon in improving the management of patrol resources. In this sense, Dallas provided a unique environment in which to examine the impact of using AVL as a management tool upon the allocation of all police patrol activities across the city. In addition, the DPD employs Compstat and has a "directed hot spots patrol" philosophy where it is the responsibility of division Commanders to plan tactical patrol allocations for officers.

In the first phase of our research we developed a method for collecting and integrating AVL data with Geographic Information Systems (GIS) data on crime, examined the reliability of AVL data by determining anomalous gaps in data when compared to police calls for service and crime, and then examined the joint trends observed between police presence and crime in police reporting areas (PRAs). The results of these endeavors are documented in the companion

'Smart Police Deployment Project: Technical Report on the Use of AVL for Deployment' (Weisburd, Groff, Jones, & Amendola, 2012). With the knowledge gained in Phase One we conducted a randomized experiment to assess whether AVL technology can help to increase the efficiency and crime control effectiveness of police patrol. We focus on two levels of analysis, beats, and hot spots. Beats form the primary unit for allocating patrol resources within the city of Dallas. Hotspots are identified as part of the Compstat process, and we examine how AVL influenced the allocation of patrol resources to crime hot spots.

THE POTENTIAL FOR USING AVL TECHNOLOGY TO IDENTIFY WHERE POLICE ARE DEPLOYED

AVL technology provides a method for identifying where police are located in real time across geography. AVL was developed in the 1980s for the transportation industry as a way of determining individual vehicle locations for a particular fleet (e.g., buses, delivery services). The methods for determining the location of vehicles for AVL have progressed over the past 30 years. Originally, AVL technology used Magnetic Strips, Multi-Lateration, Odometer-Only, Signpost-Only, and Loran C systems; but now, Global Positioning Systems (GPS) are the favored method for determining location within AVL systems (Cain & Pekilis, 1993; Johnson & Thomas, 2000).

AVL systems rely on GPS technology created in the 1980s by the United States Department of Defense for military purposes. Within GPS technology, the two major components are satellites and receivers. Originally, 18 satellites were launched in six different orbits, evenly spaced 60 degrees apart and at 20,200 kilometers in altitude. These satellites transmit on the radio frequencies 1227.60 mHz and 1575.42 mHz. The 12 hour orbit planes are inclined at 55 degrees from the Equator and now, with the current allocation of four satellites per orbit (24 total satellites), the Earth is adequately covered so that positioning can be determined at any point on the Earth's surface by using a GPS receiver.

GPS receivers use very simple mathematics in ingenious ways (Thompson, 1998). In describing the inner workings of GPS, Thompson (1998) says that each satellite sends signals on each of its frequencies indicating its position and the exact time of the signal. Signal transmission times are recorded in nanoseconds (Dixon, 1999). The receiver then records the differences in the time when it received the signal and the time when the signal was originally sent by satellite (Δt). With current technology, GPS accuracy is somewhere between 10 and 20 meters.

While the GPS receiver gathers coordinate data on the location of vehicles, without a means to capture, store, and analyze that information, it is virtually useless. The second component to an AVL system deals with the data that are captured from the satellite and how those data are transmitted to the decision-makers. One of the most common methods, also used in DPD's AVL system, is a method called polling, which requires the dispatch center to send a radio wave message to the vehicle asking for its location. The vehicle in-turn sends a message containing its geographic coordinates back to the dispatch center. This cycle repeats, vehicle by vehicle until the location of every vehicle in the fleet is known.

Since there are many companies that provide AVL technology, and because there has been very little research on the use of AVL in law enforcement agencies, it is difficult to estimate how many agencies are currently using this technology. In a scan of vendor websites and client lists, we found at least 50 police agencies that use AVL technology. As early as 1998, a technical report prepared for the National Committee on Criminal Justice Technology (Seaskate, 1998) highlighted a case study on the use of AVL in the Schaumburg (IL) Police Department. This study claimed that the department's primary objectives in implementing AVL were improved response times and increased officer safety. Of interest is the fact that the Schaumburg Police Department expressed a desire to perform "unit analysis to optimize the department's coverage and place vehicles in high-activity areas," (Seaskate, 1998, p. 109) although they had not, at the time of publishing, conducted any systematic study showing the results of the AVL on operations.

We are not aware of any systematic analysis of the use of AVL to allocate preventive police patrol, although there have been a number of evaluations of its potential to manage dispatch in response to calls for service (see e.g., Larson 1978; Larson & Franck, 1978; Larson et al., 1977; Russo 2006). Since this study began, there have been isolated examples of the use of AVL in research, for example, to document whether increased police presence was brought to specific areas in the context of assessments of a new hot spots policing strategy (see Telep, Mitchell, &Weisburd, In progress). Nonetheless, it is clear that AVL makes it possible to monitor police patrol activities and thus represents an opportunity for police managers to maximize patrol resources in cities. But a key related question is whether maximizing such patrol resources would actually have an impact on crime.

CAN POLICE PATROL IMPACT CRIME?

Until the 1970s there was a general assumption among police and police scholars that preventive patrol by police was an effective deterrent to crime (Kelling et al., 1974; Olson & Wright, 1975; President's Commission on Law Enforcement and Administration of Justice, 1967). As George Kelling and his colleagues wrote in their introduction to their Report on the Police Foundation's Kansas City Preventive Patrol Experiment:

> Ever since the creation of a patrolling force in 13th century Hangchow, preventive patrol by uniformed personnel has been a primary function of policing. In 20th century America, about $2 billion is spent each year for the maintenance and operation of uniformed and often superbly equipped patrol forces. Police themselves, the general public, and elected officials have always believed that the presence or potential presence of police officers on patrol severely inhibits criminal activity. (Kelling et al., 1974, p. 1)

Preventive patrol in police cars became the main staple of police crime prevention efforts in the decades after the Second World War. As Kelling et al. noted in 1974: "(t)oday's police recruits, like virtually all those before them, learn from both teacher and textbook that patrol is the 'backbone' of police work" (Kelling et al., 1974, p. 1). The Police Foundation study sought to establish whether empirical evidence actually supported the broadly accepted assumptions regarding the crime control effectiveness of preventive patrol. The fact that questions were raised about routine preventive patrol suggests that the concerns about the effectiveness of the police had begun to impact upon the confidence of police managers. As Kansas City Police Chief Clarence M. Kelley, later to become director of the FBI, said in explaining the need for the Kansas City Experiment: "Many of us in the department had the feeling we were training, equipping and deploying men to do a job neither we, nor anyone else, knew much about" (Murphy, 1974, p. iv).

Kelling and his colleagues, in cooperation with the Kansas City Police Department, took 15 police beats and divided them up into three groups. In five of these, called "reactive" beats, "routine preventive patrol was eliminated and officers were instructed to respond only to calls for service" (Kelling et al., 1974, p. 3). In five others, defined as "control" beats, "routine preventive patrol was maintained at its usual level of one car per beat" (Kelling et al., 1974, p. 3). In the remaining five beats, termed "proactive" beats, "routine preventive patrol was intensified by two to three times its usual level through the assignment of additional patrol cars" (Kelling et al., 1974, p. 3). When Kelling and his colleagues published the results of their study in 1974 it shattered one of the bedrock assumptions of police practitioners – that preventive patrol was an effective way to prevent crime and increase citizen feelings of safety. They concluded simply that increasing or decreasing the intensity of routine preventive patrol in police cars did not affect either crime, service delivery to citizens, or citizen feelings of security.

To understand the impact of the Kansas City Study on police managers and researchers, it is important to recognize not only that the study examined a core police practice but that its methodological approach represented a radical departure from the small scale evaluations of police practices that had come earlier. The Kansas City Preventive Patrol Experiment was a social experiment in policing on a grand scale, and it was conducted in a new Foundation that had significant resources and was backed by the well-established and respected Ford Foundation. Patrick Murphy, the distinguished police manager, and President of the Police Foundation at the time, suggests just how much the Foundation itself saw the experiment as a radical and important change in the quality of police research:

> This is a summary report of the findings of an experiment in policing that ranks among the few major social experiments ever to be completed. The experiment was unique in that never before had there been an attempt to determine through such extensive scientific evaluation the value of visible police patrol. (Murphy, 1974, p. iii)

This context, both in terms of the centrality of the strategy examined, the "quality" and scale of the research, and the prestige of the institutions that supported the study, including the Kansas City Police Department and its Chief Clarence Kelly, were to give the findings of the study an impact that is in retrospect out of proportion to the actual findings. One study in one jurisdiction, no matter how systematic, cannot provide a comprehensive portrait of the effects of a strategy as broad as routine preventive patrol. Besides, the evidence, even at the time, was mixed. Two studies, for example, both using weaker quasi-experimental designs, suggested that random preventive patrol can have an impact on crime (Dahmann, 1975; Press, 1971). Additionally, the study design was to come under significant academic criticism in later years (Larson & Cahn, 1985; Minneapolis Medical Research Foundation, 1976; Sherman & Weisburd, 1995). A key element of this criticism was that the researchers and police in Kansas City did not know whether in fact the "dosage" in the beats that were expected to gain greater patrol was in fact higher, or whether the dosage in the beats with lowered preventive patrol was actually lower (Sherman & Weisburd, 1995). This is because the police knew where they had dispatched more cars, but they could not measure whether this actually led to significant increases in the patrol time spent in any particular beat.

Another explanation for why the Kansas City Preventive Patrol Experiment failed to show a deterrent effect of preventive patrol was brought by Sherman and Weisburd (1995, p. 629):

> The premise of organizing patrol by beats is that crime could happen anywhere and that the entire beat must be patrolled. Computer-age data, however, have given new support to Henry Fielding's ([1751] 1977) eighteenth century proposal that police pay special attention to a small number of locations at high risk of crime. If only 3 percent of the addresses in a city produce more than half of all the requests for police response, if no police cars are dispatched to 40 percent of the addresses and intersections in a city over one year, and, if among the 60 percent with any requests, the majority (31%) register only one request per year (Sherman, Gartin, & Buerger, 1989), then concentrating police in a few locations makes more sense than spreading them evenly throughout a beat.

Coining the term "hot spots policing" Sherman and Weisburd argued that the police should not water down the dosage of police patrol across entire beats, but should focus it upon the specific places where crime was concentrated. Subsequent studies have reinforced Sherman and Weisburd's observations, showing a fairly constant concentration of crime in cities at a relatively small number of places. Indeed, Weisburd, Groff, and Yang (In press) argue that these concentrations are so consistent across time and across cities that we can assume a "law of concentrations of crime at place." For example, in Minneapolis, Sherman et al. (1989) found that 3.3% of the addresses were responsible for 50% of the crime calls to the police. Pierce et al. (1986) found that 3.6% of the addresses produced 50% of crime calls in Boston. Such crime concentrations are also found in cities outside the U.S. Weisburd and Amram (In press) for example, found that 5% of the street blocks in Tel Aviv produced 50% of the crime incidents. Weisburd et al. (2004) illustrated not only that crime is concentrated in Seattle at street blocks at similar levels, but that such concentrations were consistent across a long time series. They found that 50% of the crime was concentrated at about 5% of street segments each year for the

14 years studied. And about 1% of the street blocks in Seattle were chronic crime hot spots responsible for 23% of the crime over a 14 year period.

Sherman and Weisburd (1995) tested their theory about patrolling crime hot spots in Minneapolis in a large randomized field trial supported by the National Institute of Justice. The results of the Minneapolis Experiment stood in sharp distinction to those of the earlier Kansas City study. The study design was extremely strong including randomization of 110 crime hot spots of about a city block to treatment and control conditions. The treatment sites received on average between two and three times as much preventive patrol as the control sites. For the eight months in which the study was properly implemented, there was a significant and stable difference between the two groups both in terms of crime calls to the police and observations of disorder in those areas. Crime, or at least crime calls and disorder, appeared to be prevented in the treatment as opposed to the control locations. Sherman and Weisburd (1995, p. 645) concluded that their results show "clear, if modest, general deterrent effects of substantial increases in police presence in crime hot spots." They noted that it was time for "criminologists to stop saying 'there is no evidence' that police patrol can affect crime" (Sherman & Weisburd, 1995, p. 647).

Subsequent studies of hot spots policing have provided strong support to the idea that focusing police activities at places where crime is concentrated is an effective crime prevention approach. As the NRC (2004, p.250) review of police effectiveness noted: "studies that focused police resources on crime hot spots provided the strongest collective evidence of police effectiveness that is now available." A Campbell systematic review by Braga (2007) reached a similar conclusion; the vast majority of hot spots studies show significant positive results, suggesting that when police focus in on high crime small geographic areas, they can significantly reduce crime in these locations (see also Braga, Papachristos, & Hureau, under review). In Braga and colleagues' (under review, also see Braga, 2005, 2007) recent meta-analysis of experimental studies, they found an overall moderate mean effect size, suggesting a significant benefit of the hot spots approach in treatment as compared to control areas. As Braga (2007, p.18) concluded "extant evaluation research seems to provide fairly robust evidence that hot spots policing is an effective crime prevention strategy." Importantly, there was little evidence to suggest that spatial displacement was a major concern in hot spots interventions. Crime did not simply shift from hot spots to nearby areas (see also Weisburd et al., 2006).

But the evidence about the effectiveness of the use of generalized patrol resources for hot spots policing is still emerging. Most of the subsequent hot spots studies involved special units that were assigned to hot spots, and utilized some type of problem-oriented policing strategy. The Minneapolis experiment showed that if significant increases of preventive patrol were brought to crime hot spots, they would evidence less crime than control locations. Similarly, in a recent randomized experiment in Sacramento, California, (Telep, Mitchell, &Weisburd, under review) showed that patrol resources that were focused on hot spots for random 15 minute intervals (following Koper, 1995) would produce lower crime at treatment locations than control locations in the city. A randomized study in Jacksonville, Florida, also found a positive impact for preventive patrol at hot spots in the study sample, though the overall results were not statistically significant (Bruce, Koper, & Woods, 2011). But a key question that has not been examined by prior studies is whether a standard directed patrol strategy at hot spots in a city would be aided by routine information provided on how much time police are spending in specific areas and specific hot spots. In Dallas, Texas, the Police Foundation provided such information to police managers.

RESEARCH QUESTIONS:

Our study sought to increase knowledge in the two key research areas identified above. While police scholars now agree widely that preventive patrol over larger areas is not effective (Weisburd & Eck, 2004; Bayley, 1994), the introduction of AVL technology allowed us to see whether providing police managers with detailed information on actual patrol dosage would allow for more effective allocation of patrol in beats and following this significant impacts on crime. This broad research concern led us to ask four specific research questions at the beat level:

1) Does knowledge about actual police patrol time influence the time that police managers expect patrol cars to spend in patrol beats under their supervision?

Absent prior knowledge about how AVL information influences police managers, we sought as a first concern to examine whether simple expectations of patrol time would change when managers gained accurate information regarding how much time officers spent in their beats. For example, does such knowledge lead Commanders to believe that they should have more time, or less time on preventive patrol?

2) Does knowledge about actual police patrol influence the amount of patrol delivered in a beat area?

We began with the assumption that knowledge about patrol delivered in a period immediately before allocations of patrol resources were made would aid managers in more efficiently and effectively managing preventive patrol. The logic here was that knowledge about actual police patrol would provide a management tool for holding officers accountable. In a police agency where accountability mechanisms such as Compstat were in place, this knowledge could be used to make sure that the patrol force was actually following the dictates of police Commanders. It is important to note that in Dallas, the system developed also tried to systematically match crime problems in beats with patrol presence.

3) Does knowledge about actual police patrol allow managers to gain greater consistency between the amounts of patrol that they request in any police beat with the actual amount of patrol delivered?

If police managers have access to an accountability mechanism that tells them whether the amount of patrol gained in any beat area was consistent with what they requested, we anticipated that the result would be a stronger consistency between patrol expectations and patrol delivery in a beat. We expected that police managers could use such information to better regulate patrol resources, and accordingly to gain greater consistency between what they requested and what was actually done by patrol officers.

4) Does knowledge about actual police patrol lead to crime reductions in the experimental beats?

A key question for any innovation in policing is whether it actually aids the police in its job of preventing and controlling crime. Our assumption here was that if AVL aided police managers in more effectively and efficiently allocating police patrol, it would also impact upon crime rates. We checked this even though admittedly the research evidence for the relationship between police presence and crime is weak at areas as large as beats.

As noted above, we also wanted to test whether AVL technologies could be used to enhance the effectiveness of hot spots policing. Directed patrol approaches have become a standard feature of modern American police agencies (Bureau of Justice Statistics, 2007; Kochel, 2011; Weisburd & Lum, 2005). We thought AVL provided an opportunity to more effectively apply hot spots approaches using broad patrol resources.

We examined four additional research questions at the level of hot spots:

5) Does knowledge about actual police patrol influence the time that police managers expect patrol cars to spend in directed patrol areas in their beats?

Does AVL knowledge about patrol lead to a change in the amount of time that managers expect patrol officers to spend in hot spots locations? Again, knowledge about the reality of police preventive patrol might lead Commanders to change their expectations regarding how much patrol they could successfully bring to hot spots in their beats.

6) Does knowledge about actual police patrol influence the amount of actual patrol delivered in a hot spot area?

We assumed, as was the case for beat area allocations, that knowledge about patrol delivered in a period immediately before allocations of patrol resources were made would aid managers in more efficiently and effectively managing preventive patrol in the following week. This again presumes that knowledge about where the police are will help Commanders to manage patrol resources more efficiently and effectively.

7) Does knowledge about actual police patrol allow managers to gain greater consistency between the amount of patrol that they request in any directed patrol area and the actual amount of patrol delivered?

If police managers have access to an accountability mechanism that tells them whether the amount of patrol gained in any hot spot area was consistent with what they requested, we expected that the result would be a stronger consistency between expectations of patrol that would be delivered and actual patrol delivery at that place.

8) Does knowledge about actual police patrol at hot spots lead to crime reductions in the directed patrol areas in the experimental beats as contrasted with the control beats?

Given the strong prior evidence about hot spots policing, we assumed that if AVL led to increased time spent at crime hot spots it would also lead to lower crime rates in those areas.

Experimental Design

The Study Site And Experimental Period

We designed the experiment in collaboration with the Dallas (Texas) Police Department (DPD). Dallas is the third-largest city in the state of Texas and as of 2010, the ninth largest (based on population) in the United States (U.S. Census, 2010). Dallas and its surrounding area are mostly flat lying at an elevation ranging from 140 to 170 m which reduces the likelihood of AVL dead spots due to topography. The city has a majority white (approximately 51%) population of approximately 1.2 million people (U.S. Census, 2010) that sprawls over 385 square miles. The city is the main cultural and economic center of the Dallas-Fort Worth-Arlington metropolitan area. The DPD has approximately 3,266 sworn officers and 617 civilians who are spread out throughout the seven divisions. The violent crime rate for 2010 was 7.01 per 1,000 residents.[2]

The DPD has been using AVL technology since 2000 and has AVL installed in virtually all patrol cars, currently 873 vehicles. The DPD has data archived back to the AVL program's inception. Ample time has elapsed to address various issues including possible obstruction by officers of AVL technology, and officer/union resistance based on AVL technology being a possible threat to their personal freedoms on the job due to its ability to capture and monitor GPS data. Through various discussions with IT staff and other personnel at DPD, there has been no indication that these issues still remain.

A marked benefit of using Dallas as our experimental site is that the department has fully implemented Compstat with routine meetings for assessing crime problems. Compstat provides a management strategy to hold division Commanders accountable for deployment and crime control in their respective districts. DPD essentially operates two versions of Compstat including a division-wide meeting which is held every Tuesday and a department-wide meeting every Thursday. In the divisional meetings, the watch Commanders, sergeants, or other designees report to the division Commander about their respective watch and related crime stats, as well as details about specific beats, sectors, etc. In the department-wide weekly meetings, each division Commander (or designated division representative) reports to the Chief

[2] Part I violent crimes in the FBI Uniform Crime Reports (2010) are murder, rape, robbery, and aggravated assault. In 2010, Dallas was 19th out of the 58 largest cities reporting to UCR (excludes Chicago, IL).

about particular activity and/or operations going on within their respective division. In addition, a short segment is periodically allotted during this meeting for a specific guest who is allowed to speak about a particular issue or concern to the command staff, which serves as a form of community engagement on behalf of DPD.

DPD has a "directed patrol" philosophy where it is the responsibility of division Commanders to actively manipulate patrol to meet emerging problems and this process is reviewed weekly. The underpinnings of this philosophy include the conceptual idea that a car or an "element" should be available to service each beat at all times when possible to provide efficient response time to calls for service. Emerging problems are quickly identified and evaluated by the weekly stats compiled by their crime analysis division which includes several crime analysts, a database analyst, and GIS specialists. The Commanders identify specific areas or hot spots that need additional patrol resources on the basis of geographic and temporal crime information and routinely request that additional resources are sent to those places.

Since the DPD has a nested hierarchy of geographic units, the first decision involved identifying the 'best' unit at which to conduct the area level portion of the experiment. The research team and DPD command staff met two separate times to discuss the relative merits of police beats versus police reporting areas as the experimental units in the study. During those conversations we learned the Dallas Police Department uses Staff Wizard® software to conduct yearly patrol allocation of patrol resources. The software factors in calls for service, crime, and overall numbers of officers to achieve the optimum level of patrol for each beat. Each Division Commander then makes beat level deployment decisions using the allocated number of patrol officers. While the Division Commanders have ultimate control of the allocation, operationally it is the division Lieutenants or Sergeants who make the weekly staffing decisions about which beats will get more or less police presence. Given the focus on beats in deployment decisions, we decided to design the first level of our experiment around beat level changes in deployment.

After those initial meetings, we worked directly with one Deputy Chief and one Lieutenant to get the experiment underway. During the course of the experiment, members of the research team made several visits to DPD. The goal of some trips was to provide training to Sergeants on filling out the deployment forms and other trips were made to interview Lieutenants and Deputy Chiefs regarding their use of AVL to aid with deployment decisions.

While the major decisions about overall deployment of patrol officers are made at the beat level, each Division within DPD holds weekly Compstat meetings to discuss emerging crime problems and evaluate on-going ones. As part of that meeting they routinely identify problem places in need of additional police attention. This identification of problem places is the key to our hot spots analyses. After negotiation with the DPD it was agreed that in each Division and in each watch (there are three main watch times per day) police Commanders would document up to five pressing problem areas that required additional preventive patrol resources.[3] They would also identify the number of hours that officers were to be assigned to those areas (see below).

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[3] In discussions with the PD it was agreed that asking for division commanders to document more than five problems would threaten the integrity of the reporting system, since it would create a burden for the division commanders. A limit of five problems was seen as a sufficient number for each division, watch and weekly assignment. In practice, division commanders could assign more than five hot spot areas.

As in other police departments there were many other initiatives underway in Dallas at the time of our experiment. However, because of the randomization of beats to treatment and control we expect the likelihood of such initiatives affecting beats would be systematically biased.

The experiment was originally designed to last 16 weeks. However, with four weeks left to go, we were informed that the Chief of Police planned to leave the department before the full intervention period could be completed. Given the upheaval that frequently accompanies a change in leadership; we decided to end the experiment after 13 weeks of full study implementation (March 22 to June 21, 2010). We believe that 13 full weeks of data was enough to allow for a meaningful assessment of the interventions, an assumption which is borne out by the study results below.[4]

Study Units of Analysis: Beats and Hot Spots

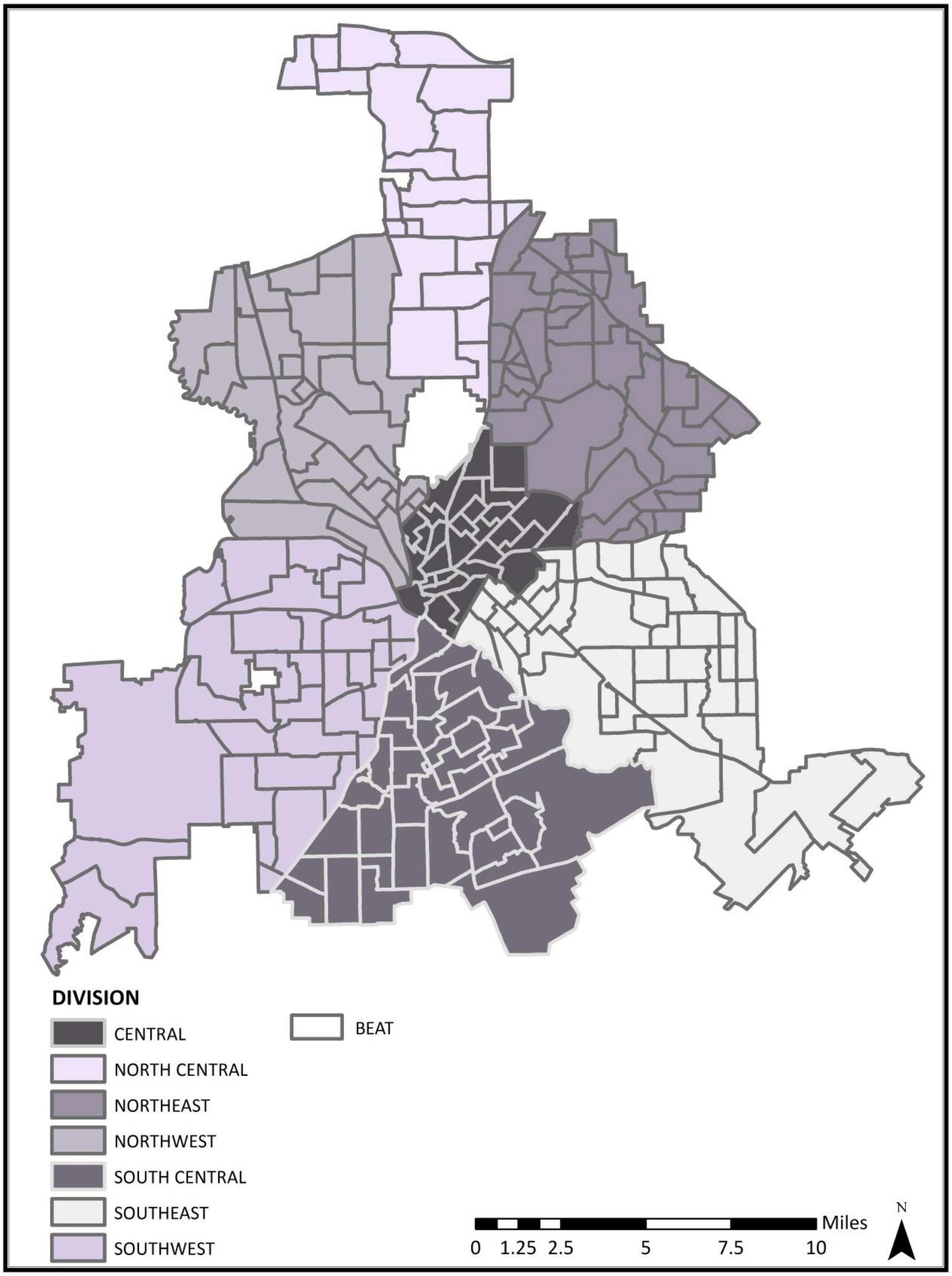
The DPD is broken into seven (7) patrol divisions and the study used 232 beats out of 234 (see Figure 1). Two beats were deleted from the study because they were composed primarily of water. The Southeast patrol division has the most beats at 42 beats followed by Northeast (41) Southwest (37), South Central (32) Northwest (30), Central (29), and North Central (21). The beats are realigned every few years. The last major realignment was done in October of 2008. As a result the study uses the 2009 beat boundaries. Assignments are given to officers by beats. Some factors that are taken into consideration when realigning beats include

[4] We collected 13 weeks of data for both the beat experiment and the Compstat hot spots test. One week of hot spots data was corrupted and had to be dropped leaving 12 week of data for that portion of the research.

workloads and how many minutes, on average, are spent per call. In Dallas, beats are on average about 1.40 square miles and range from .13 to 8.84 square miles. Crime varies dramatically across the 232 beats. For example, in 2009 the total crime ranged from 162 to 1,714 across the beats. This wide disparity in the intensity of crime in the districts led us to define crime trends as a key "blocking" factor for our study (see below).

For the purposes of the experiment, the hot spot areas identified during Compstat meetings as candidates to receive directed patrol area were supposed to be very small geographic areas. For example, a hot spot in this case would be defined as a single intersection, or a single street segment. In practice, Commanders sometimes defined long address ranges such as the 100 to 700 block of a particular Avenue. When such data were provided we broke up the range to smaller geographic units. For example, we would identify seven specific hot spot areas for the example above, consistent with the specific hundred block street segments. In the following week the Commander would receive patrol and crime statistics on the specific street segments in the areas identified.

Figure 1: Police divisions and beats in Dallas, TX



Quantifying Police Presence Using Intended Deployment

A key issue in our study is the impact of AVL on expectations regarding the deployment of patrol resources. Accordingly, we needed to develop mechanisms for collecting data on how much time police Commanders expected patrol officers to spend in specific areas. Following our research questions, we measured intended deployment at two levels of analysis, beat and hot spot.

Measuring Beat Level Deployment

Beat level intended deployment information was collected via a computer information system developed as a collaborative effort between the Police Foundation research team and DPD's Information Technology Division. The deployment application was a web-based, intranet application (only accessible by department personnel) developed to obtain information about planned allocation of resources (i.e., cars) during the experimental period (see Figure 2). The main purpose of this module was to try to capture real operational figures or "deployment estimates" about how each division planned to allocate their elements/patrol cars during each shift on a daily basis. This information was later quantified and used to inform the Deployment Tracking Report described in the next section. Each day DPD personnel entered the patrol deployment they intended to achieve based on the resources available.[5]

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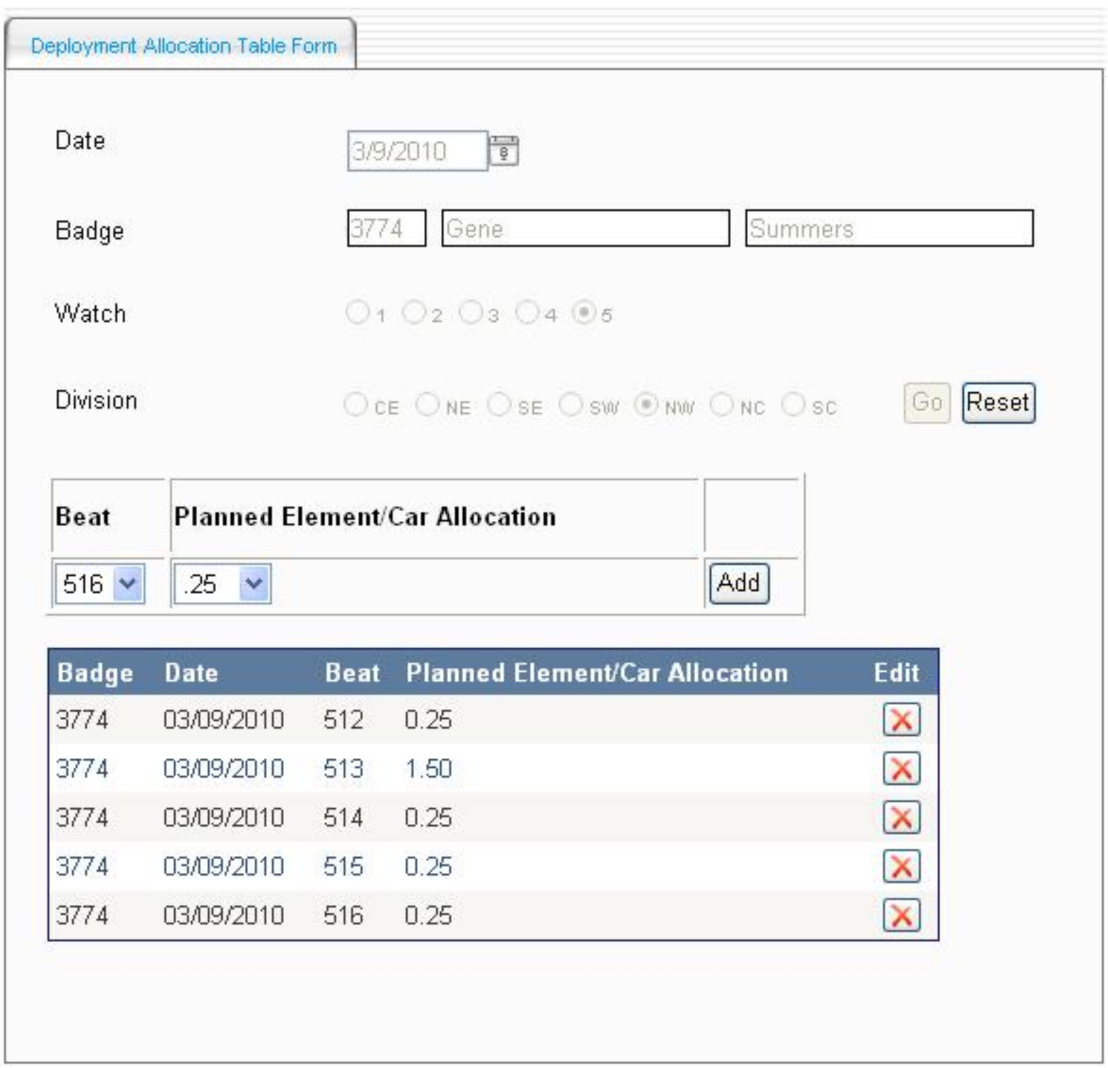
[5] While beat level deployment decisions were made at the Lieutenant and Sergeant levels, the task of entering the data into the automated system typically fell to Administrative Sergeants. The day was split into three equal time periods, 0800 to 1559, 1600 to 2359, 2400 to 0759. However, as is the case in many police departments, DPD runs five overlapping shifts. Overlapping shifts were allocated using a standard formula (see Appendix A).

Figure 2: Sample Deployment Module Entry



Measuring Hot Spot Level Deployment

Information about patrol allocations to hot spots originated in the weekly Compstat meetings held by each Division Commander. After problem places/hot spots were identified in the meeting, the Division Commanders requested specific amounts of increased attention to those places. We worked with DPD personnel to create a form capable of capturing this dynamic allocation of police resources which 'fit' into their current workflow. The purpose of this form was to get both a qualitative and quantitative understanding of how much time the department wanted to spend on each of these places or intersections they listed, the type of problem(s) occurring, and the type of attention (i.e., surveillance, directed patrol, traffic enforcement) planned to address the problem(s). The result of those collaborations was the 'Compstat Target Form' on which they listed the top places or intersections of interest (no more than five total allowed) that each division and each watch were planning to focus on each week based on crime activity and other department priorities (see Figure 3). These forms were collected for all five watches, however 4th and 5th watch entries were collapsed into whichever watch they selected as their primary watch in terms of command.[6] The forms were usually completed by either the Division Commanders, Administrative Lieutenants, or other designated personnel. In the case where Commanders identified large geographic areas as directed patrol areas, we not only divided up the areas into smaller hot spots, but also divided up the number of hours of patrol according to the number of hot spots identified.

[6] In most cases the 4th watch reported to the 3rd watch commander staff so the designated officer would have selected the 3rd watch option on the target form they submitted. Other 4th watch officers reported primarily to the 1st watch command staff; thus, the designated officer would have selected the 1st watch option on the target form.

Figure 3: Compstat Target Form

****REVISED** WEEKLY COMPSTAT TARGET FORM**

PERIOD: May 19th- May 23rd (Wed. through Sunday) NAME: N/A CONTACT NUMBER: N/A

The purpose of this form is to provide information based on your weekly, divisional Compstat meetings. This information will be used to assist the Police Foundation in providing you feedback about the amount of presence (in total hours) specific places or intersections received during this period.

Please select division and watch (highlight or bold your choice):

DISTRICT: NORTHCENTRAL SOUTHCENTRAL SOUTHWEST NORTHWEST SOUTHEAST NORTHEAST CENTRAL

WATCH: 1st WATCH 2nd WATCH 3rd WATCH

Please list the target places OR intersections (maximum of five) of greatest concern in your division below. A place would be any area which is not an intersection such as 1) a hundred block or set of hundred blocks, e.g. 4400 -- 4700 Ross Avenue; 2) a park, 3) a corridor/street segment; etc. Then for each, please indicate the total amount of attention (in total hours) you want directed to each place over the 5 day period for this watch only. **DO NOT LIST ENTIRE BEATS, SECTORS, OR TAAG AREAS as we will be unable to provide feedback on these larger geographic areas for this study.**

Places OR	Intersections	Beat	Description of Problem to be Addressed	Amount of Attention (Hours)	Type of Attention
	Columbia/Beacon Report Area 1157	112	Property Offenses	10	Directed Patrol
	Victor/Reiger Reporting Area 4518	114	Residential Burglaries	10	Directed Patrol
	Cole/Cedar Springs Rd Reporting Area 2038	2038	Property Offenses	10	Directed Patrol
	Good Latimer/Taylor Reporting Area 2090	135	Property Offenses	10	Directed Patrol
	Capitol/Fitzhugh Reporting Area 1181	146	Property Offenses	25	Directed Patrol

Please email to gjones@policefoundation.org or fax to: Greg Jones, Police Foundation, 202-296-2012

QUANTIFYING ACTUAL POLICE PRESENCE USING AVL MEASURED DEPLOYMENT

Automated Vehicle Locator (AVL) technology allows us to capture GPS data, which gives us a unique measure of police presence. These data include latitude/longitude position, speed of the vehicle, and a unique vehicle identification number. When vehicles are stationary, a data point is created every 15 seconds. As a vehicle begins to move, a data point is created for every 300 meters that the vehicle travels. The challenge to using AVL is transforming the volume of raw coordinates into actionable information that is immediately useful (Groff, 2009).

The Dallas Police Department wrote a program which aggregates time spent by police officers in quarter mile (1,320 foot) square grid cells that covered the city. Department personnel ran this program and supplied the research team with aggregated time spent in each beat and each grid cell.[7] Actual police presence was measured via AVL data collected from the patrol vehicles. AVL measured data (police presence data) included the following: Assgn (assigned), Enr (en route), At Scene, Assgn 2nd Loc (assigned to second location), Enr 2nd Loc (en route to second location), At Scene 2nd Loc, To Fac (to facility), MA (multi-assign), Clear (available to take calls).[8]

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[7] We attempted to use geographic information systems to measure the elapsed time spent in each police reporting area (PRA) but the complexity of the program meant it ran very slowly. Instead we used a program written by Lt. Rupert Emison in the Chief's Office of DPD. More details about the methodology he used are available in the companion methodology report (Weisburd, Groff, Jones, & Amendola, 2012).

[8] During the first two weeks of the experiment, only calls designated as "At Scene","Enr" and "To Fac" were used to delineate Call Time. In Week 3, we began using an expanded definition contained in the text. Throughout the experiment, we excluded time with the following status codes: "Station" and "OOS" and "At Fac". Any analyses which discuss 'discretionary time' versus 'time on calls' use the status code "Clear" to represent free time. Data do not contain information about marked elements from the Gang Unit, Traffic Unit, SWAT Unit, Disruption Unit, and Auto Theft Unit.

Beat and hot spot level police presence were measured using the previously mentioned grid of quarter mile cells. Police presence was first aggregated to the grid using the pings from the car's AVL. If two subsequent pings were in the same grid cell, the intervening time period was assigned to the grid cell. When pings crossed from one grid cell to another the amount of time was assigned proportionately to each cell using geometry and trigonometry. The amount of time spent by patrol cars in each grid cell was summed to represent grid cell level police presence. Beat level police presence was calculated by aggregating the grid cells within each beat.[9]

AVL measured patrol constituted our primary measure of police patrol presence. The measure itself allowed us to differentiate between discretionary time and time when the officers were assigned to a call. It is important to note that the measure captures all police presence in a beat (not just that of the officers assigned to a beat). DPD has AVL technology in virtually every patrol car; thus, this is a measure of activity by marked police units.[10]

TOTAL CRIME

Total crime included all homicide, rape, robbery, aggravated assault, burglary, theft, unauthorized use of motor vehicle (UUMV), auto theft, burglary of motor vehicle (BMV),

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[9] Because beat boundaries follow streets and grid cell boundaries do not, there was not an exact match. Grid cells were assigned to beats containing the largest proportion of the grid cell area.

[10] It is important to note that patrol cars are sometimes used for special operations (deployment other than patrol) and as such patrol cars on these duties would be included in our measure of police presence. Because they are marked cars, they still contribute to the level of visual police presence at a place.

narcotics/drugs, vandalism/criminal mischief, and assault. DPD's Crime Analysis Unit geocodes all offense reports and arrest reports and they have a geocoding hit rate of 99% after data cleaning. They attribute this high hit rate to a clean, accurate street centerline file that is shared and maintained by the city government. To account for cases of property crime for which an exact time of occurrence was unknown, we conducted an aoristic analysis of the total crime data.[11] We used total crime data for 2009 as the basis for establishing the blocking scheme. We also used total crime as an outcome measure in the evaluation of whether AVL measured feedback on deployment achieved would reduce crime.

We measured crime using two distinct time periods. One time period was represented as a seven day week (Monday – Sunday) and the other a five day week (Wednesday – Sunday). Since deployment decisions were made during a Tuesday Compstat meeting, the five day week reflected the days immediately after a deployment was changed. The seven day week represented the entire time until new information was received and the deployment potentially changed.

Creating Experimental Blocks Using Trajectory Analysis of Total Crime

As noted above, our initial analysis of crime data in Dallas showed that crime rates varied a good deal between the beats. Such large variation in the baseline for a key indicator that was also strongly correlated to patrol allocations led us to use a block randomized design for our

[11] Aoristic analysis involves spreading the crime risk equally across the hours of the timespan by assigned each hour a portion of the probability the crime occurred in that time period (for more details see Ratcliffe, 2000, 2002).

study (Gill & Weisburd, In Press; Weisburd & Gill, In Progress; Weisburd & Taxman, 2000). Block randomized designs allow a researcher to increase confidence in the equivalence of study groups in an experiment, by first defining broad categories of cases and then randomizing units within those categories. For example, in our case if we could identify beats with similar crime trends, we could randomly allocate equally beats in groups that reflected similar trajectories of crime over time. This approach also has the benefit of increasing the statistical power of a study (Gill &Weisburd, In Press; Weisburd & Gill, In Progress).

We relied upon group-based trajectory analysis (Nagin, 1999; Nagin & Land, 1993; Nagin & Tremblay, 2005) as a technique for identifying broad groupings of beats for randomization in our study. Formally, the model specifies that the population examined is comprised of a finite number of groups of individuals who follow distinctive developmental trajectories. Each group is allowed to have its own offending trajectory (essentially a chart of offending rates throughout the time period) described by a distinct set of parameters that are permitted to vary freely across groups. This type of model has three key outputs: the Bayesian Information Criterion (BIC), the estimated proportion of the population belonging to each group (also called the odds of correct classification (OCC)), and the posterior probability of belonging to a given group for each individual in the sample. The posterior probability, which is the probability of group membership after the model is estimated, can be used to assign an individual to a group based on their highest probability. In this context, the posterior probability describes the likelihood that any beat would fall within a specific trajectory (for more technical detail regarding the trajectory analysis, please see Appendix 1).

Trajectory analysis is less efficient than linear growth models but allows for qualitatively different patterns of behavior over time. There is broad agreement that delinquency and crime is one such case where this group-based trajectory approach might be justified, in large part because not everyone participates in crime, and people appear to start and stop at very different ages (Muthen & Muthen, 2000; Nagin & Tremblay, 1999; Nagin, 2005; Raudenbush, 2001). Originally developed for application to individuals, group-based trajectory analysis was first applied to micro-level places by Weisburd et al. (2004) and Griffiths and Chavez (2004). Using weekly total crime data for 2009, we employed group-based trajectory analysis to identify groups of beats based on total crime figures.[12]

We identified four different developmental groups at beats in 2009 (Figure 4).[13] One group represents beats which have very low weekly crime levels. This very low crime group has 21 beats (9.8%) in it and its members experienced roughly three crimes to six crimes per week. The 94 low crime beats (40.3%) ranged from a low of six to a high of nine crimes per week. The medium crime group contains the largest number of beats (n = 100, 42.6%) and ranges from 9.5 to just over 13 crimes per week. Seventeen beats (7.3%) were significantly higher than the medium crime group ranging from 15 to 25 crimes per week.

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[12] The analysis complexity and number of trajectories may be dramatically affected by the time unit of analysis chosen for the trajectory analysis; because our research focused on weekly deployment decisions, we conducted trajectory analysis using aggregate measures for each beat by week for 2009. We feel that this time unit provides accurate findings which also correspond with our intervention, for which we provided weekly police presence measures to police commanders (see discussion later in regards to "new" deployment).

[13] We used ProcTraj in SAS to conduct the trajectory modeling. Zero-inflated Poisson models truncated at 35 crimes per beat per week were applied to the data. After diagnostic testing, we determined quadratic models fit better than linear or cubic ones. Extensive sensitivity testing was conducted using a number of groups ranging from two to nine. The best fitting solution was provided using four groups (see Appendix 1 for more detail).

Figure 4: Results of the Trajectory Analysis on Total Crime

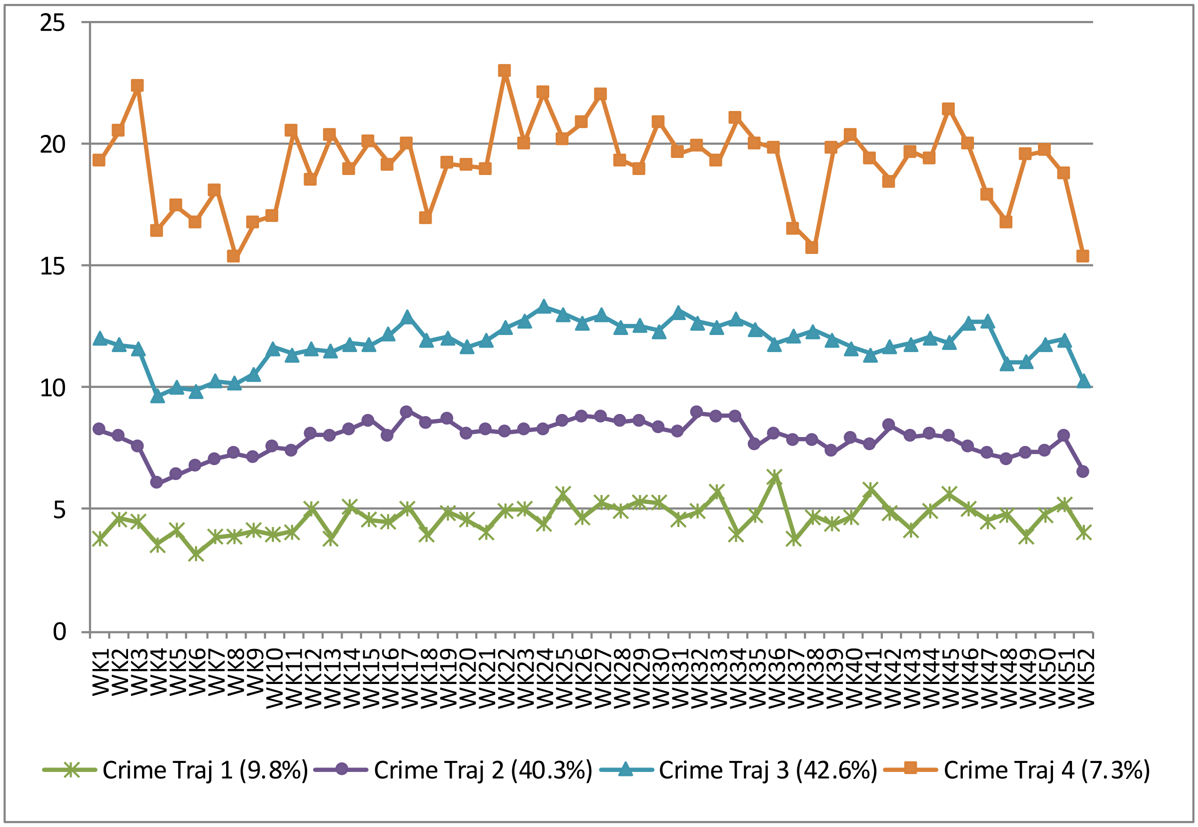

Figure 5 depicts the spatial distribution of the beats using their trajectory classification.[14]

Members of the very low crime trajectory group are spread out across the city with a cluster

[14]While trajectory analysis is useful in grouping beats by temporal crime pattern, it is unable to examine the spatial pattern of group members. We used a variety of spatial techniques to examine the spatial patterns of trajectory group membership. Since group membership is a limited categorical variable, we are constrained in the techniques we can use to examine the distribution of street segments on the variable of interest. A series of formal tests of the spatial distribution of crime events was employed to characterize the degree of spatial autocorrelation in the distribution of trajectories and total crime. We used both a global (Moran's *I*) and a local technique (local indicator of spatial association, LISA). Local statistics are designed to examine the second order effects (i.e., local relationships) related to spatial dependence (Bailey & Gatrell, 1995; Fotheringham et al., 2000). The LISA statistic is calculated in order to measure the degree of spatial autocorrelation in the pattern (i.e., how likely a beat of one group is to be near a beat of the same or any another group). We examined the degree of spatial autocorrelation among a beat's trajectory membership and found significant but weak positive spatial autocorrelation using the global measure of Moran's *I* for all groups except group 4 (at p< .01) and for total crime across beats (p < .001) (see Technical Report

just south of downtown. There is a wide almost unbroken swath of low crime trajectory group members in the south central portion of the city with additional members found in all other cardinal directions. The medium crime trajectory members are found in large clusters to the northeast, northwest, southeast and southwest of the city center. The high crime trajectory group members are dispersed and found in clusters of no more than two beats. Interestingly, there are no high crime trajectory group members in downtown Dallas.

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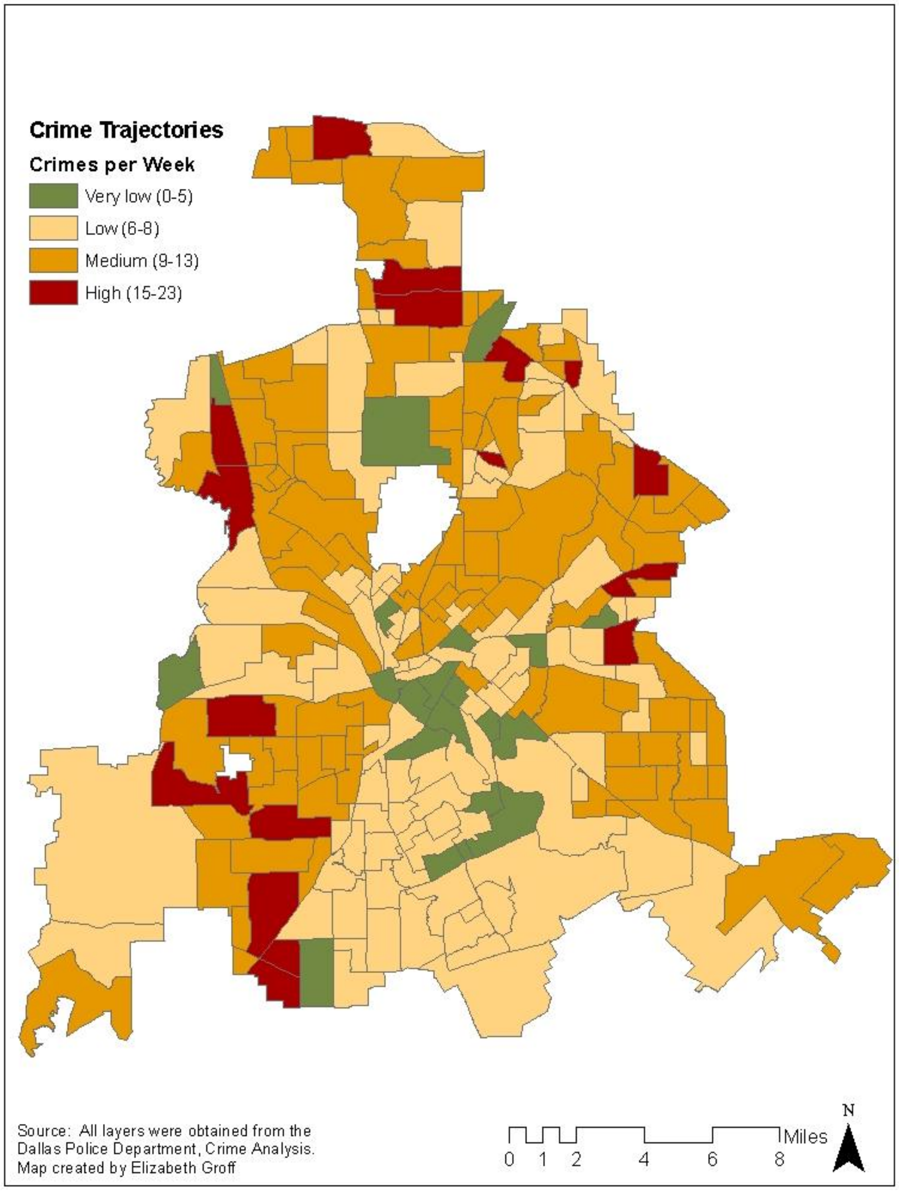
for more details). The LISA analysis revealed the dominant relationship was one of negative spatial autocorrelation. Two exceptions were a cluster of positive spatial autocorrelation among group 2 beats in the south central area of Dallas and numerous significant clusters of group 3 beats around the city (see Technical Report for more details). Moran's *I* and LISA statistics were calculated in GeoDa 0.9.5-i®. All maps of the analyses were created in ArcGIS 9.3®.

Figure 5: Spatial Distribution of Crime Trajectory Groups



RANDOM ASSIGNMENT OF BEATS

The 232 beats were allocated equally to two groups using the pseudo-random number generator in Excel. The distribution was conducted in four statistical blocks, based on the results of the trajectory analysis. One group of beats was the treatment group (N=116) and police managers of those beats received information about the actual patrol levels received in the previous week to use in their deployment decisions (see below). The other group, the control beats (N=116), police managers did not receive information about police presence as measured by AVL. Police managers were briefed on the design of the study and asked to report their daily staffing allocations to beats for both treatment and control areas. Patrol officers were not informed of the study.

STATISTICAL POWER

An important concern in any experimental study is whether the research design allows for a statistically powerful test of the hypotheses examined (Lipsey, 1998; Weisburd & Britt, 2007). It is difficult to calculate the expected power in a block randomized experiment with unequal size blocks because most conventional programs do not allow the creation of unequal block sizes in calculations. But more important, the influence of block randomization on statistical power will depend on the actual correlation between the blocking factor and the outcome variable.

A conservative approach given these limitations is to calculate power levels using a simple randomization model. This provides a low end estimate of the statistical power of the study.[15] Using this approach, at the beat level our study is strongly powered for detecting what are generally defined as large (Cohen's D=.80) and medium (Cohen's D=.50) effect sizes. The statistical power level is almost 100% for a large effect size, and .98 for a medium effect size.

[15] We use Power and Precision (http://www.power-analysis.com) to estimate the statistical power of the study.

Smaller effect sizes provide less confidence. For a standardized mean effect size of .40 the power level is still .90, but an effect size of .30 leads to a power level of .68. This is sometimes considered acceptable, but is below a .80 level that is generally considered a good standard for a well-designed study (Weisburd & Britt, 2007).

Because of the larger sample size (see below), analysis at the hot spot level produces a high level of statistical power at even very small effect sizes. For example, there is a power level of .94 to detect a mean standardized effect size of .20, and a power level of almost 1.0 to detect an effect of .30.

Treatment: Feedback on Deployment Levels Achieved

The first step in designing the treatment was to work with a committee from the department to discuss the information about measured deployment to be provided on a weekly basis.[16] The committee was appointed by the chief and consisted of Commanders in the department who were knowledgeable about the present patrol deployment strategy. After a series of meetings with DPD field Commanders, we created two feedback forms which were given to the DPD Division Commanders on a weekly basis. Both forms contained information about AVL measured deployment, one for beats and the other for Compstat hot spot areas.

Treatment Provided For Beats

[16] The companion report describing the research effort contains the details of collecting information from DPD and producing the reports.

Using GPS data at the end of each project week, the research team produced a deployment report which was provided to the Division Commanders responsible for each treatment beat. To preserve the integrity of the experiment, the Division Commanders received no information about police presence in the control beats. Two beat level deployment reports were developed. One form consisted of a simple listing of the amount of police patrol intended and received by each Beat and provided specific information on both call time and discretionary time spent by police officers in each beat (Figure 6).

Figure 6: Sample Deployment Tracking Report (DTR)

Division Commanders' Deployment Tracking Report **(Treatment Beats Only)**
Central Division_2nd Watch
Reporting Period: **May 12 - 16, 2010**

Instructions: Upon receiving this report, please review the total hours that officers were present in the associated beats in relation to the hours that were allocated (number of officers assigned across the five-day period). Then please: 1) indicate with an "X" whether the coverage is sufficient or if you would like your watch commaders to increase or decrease coverage (number of officers assigned); 2) share this information with your Watch Commanders and/or Station Sergeants; and 3) e-mail the completed form to gjones@policefoundation.org

					To be completed by Divison Commanders: based on upcoming period May 19-23		
Beat #	**Total Hours Allocated**	**Actual Call Time (Hours)**	**Actual Discretionary Time (Hours)**	**Total Actual (Hours)**	**No Change Required**	**Increase Coverage**	**Decrease Coverage**
112	31.89	28.13	11.55	39.69			
114	31.89	20.83	7.54	28.37			
115	31.89	33.97	7.73	41.70			
123	33.69	4.80	1.45	6.24			
132	14.94	32.17	22.24	54.41			
133	14.94	22.20	14.24	36.43			
135	14.94	32.87	16.81	49.68			
136	14.94	16.83	4.27	21.09			
141	11.94	20.49	8.93	29.42			
142	11.94	11.87	8.04	19.90			
144	11.94	22.20	7.50	29.70			
145	11.94	19.13	12.89	32.02			
146	11.94	7.58	5.29	12.87			
151	12.48	71.88	9.23	81.11			
154	12.48	31.95	21.09	53.04			
156	12.48	14.71	18.45	33.16			
Totals	**286.26**	**391.60**	**177.24**	**568.84**			

This table provides information to assist deployment decisions for treatment beats only. "Allocated' is based on the number of officers assigned to the beat and can be in whole numbers or fractions. "Actual" is the total number of hours spent over the five-day period.

The other is a form we designed to organize the information into nine categories (Figure 7) with the goal of making it easier for DPD management to identify beats which were over or under their deployment goals. The report categorized the beat based on the level of crime and police presence from the previous five day reporting period (Wednesday – Sunday). The report is divided into nine grids, each representing a combination of a certain level of crime and police presence (e.g., low crime/high presence, medium crime/low presence). The high-high, medium-medium, and low-low beats are ones where the two measures are in sync. The other Beats indicate areas that are assumed to need adjustment (or that something else is happening there). These data were reported for the following shifts: Midnight to 8am (2400-0759), 8am to 4pm (0800 – 1559), and 4pm to Midnight (1600 – 2359).

Figure 7: Sample Crime and Presence Matrix

Police Presence Information for Treatment Beats

Central Division: 1st Watch

Five-Day Period: May 12-16, 2010

LOW CRIME/HIGH PRESENCE	MEDIUM CRIME/HIGH PRESENCE	HIGH CRIME/HIGH PRESENCE
Ranges: Crime (0)/Presence(27.72-278.49)	Ranges: Crime (1-5)/Presence (27.72-278.49)	Ranges: Crime (6-17)/Presence (27.72-278.49)
	115, 135, 136	132, 133, 142, 144, 154
LOW CRIME/MEDIUM PRESENCE	**MEDIUM CRIME/MEDIUM PRESENCE**	**HIGH CRIME/MEDIUM PRESENCE**
Ranges: Crime (0)/Presence (11.85-27.71)	Ranges: Crime (1-5)/Presence (11.85-27.71)	Ranges: Crime (6-17)/Presence (11.85-27.71)
	114, 145, 151, 156	123, 141
LOW CRIME/LOW PRESENCE	**MEDIUM CRIME/LOW PRESENCE**	**HIGH CRIME/LOW PRESENCE**
Ranges: Crime (0)/Presence (0-14.32)	Ranges: Crime (1-5)/Presence (0-14.32)	Ranges: Crime (6-17)/Presence (0-14.32)
	112, 146	

1 The level of crime is indicated first followed by the level of police presence. Ranges are provided for crime and presence in each category based on the corresponding data. Crime range = total count of crime over the five-day period/Presence range = average number of minutes of police presence per hour over the five-day period. This information is for use by Dallas Police Department only.| Police Foundation

These deployment reports assisted the Commanders with making re-deployment decisions regarding police patrol to better reflect deployment goals. Most importantly, they provided Commanders the means to employ AVL technology to aid their on-going deployment decision making process. Essentially, the AVL technology allowed the Police Chief as well as the Commanders a means of accountability over where police patrol resources were allocated over the span of the project.

TREATMENT PROVIDED TO COMPSTAT HOT SPOTS

In order to investigate the utility of AVL data for obtaining specific amounts of police presence at hot spots, we also provided a report comparing the intended deployment for each hot spot area with the police presence as measured by AVL data (see Figure 8). These reports were sent to Commanders responsible for each treatment beat on Monday so they would have time to review them before their Tuesday morning Compstat meeting. The report provided feedback on the amount of police presence at certain places or intersections vs. amount actually received at those places or intersections. This report is based upon the specific areas of interest listed on the weekly Compstat Target Form (see Figure 3). In addition, the report included the following information: 1) beat where the place or intersection is located, 2) corresponding grid ID, 3) type of problem(s), 4) type of attention planned, 5) the amount of attention requested by each watch, 6) number of crimes that occurred, and 7) how much attention was received broken down by discretionary time, call time, and total hours. The grid ID field referred to the position of the place on a grid of quarter mile cells used by DPD's crime analysis section.

Figure 8: Sample Compstat Target Form

COMPSTAT FEEDBACK REPORT

CENTRAL DIVISION

WATCH 3

REPORTING PERIOD: May 12-16, 2010

This report provides information about the amount of attention desired during the period May 12-16, 2010 for a specific place or intersection via the Compstat Target Form (CTF). Also listed is corresponding information for each place or intersection including beat, problem, GRID #, etc. Most importantly, there is information provided about the amount of attention and crime actually received near, at, or around that place or intersection. The amount of attention and crime received for each place or intersection from other watches is also provided .

SUBMIT DATE	ORDER	PLACE	INTERSECTION	PROBLEM	TYPE OF ATTENTION	BEAT	GRID ID
5/13/2010	1	RA 2090	Good Latimer/Taylor	PO	DP	135	7864
5/13/2010	2	RA 2038	Cole/Cedar Springs Rd	PO	DP	122	8409
5/13/2010	3	RA 4518	Victor/Reiger	RB	DP	114	8530
5/13/2010	4	RA 1157	Columbia/Beacon	PO	DP	112	8531
5/13/2010	5		Capitol/Fitzhugh	PO	DP	146	8854

AMOUNT REQ	ORDER	DISC. TIME W1	CALL TIME W1	TOTAL HRS W1	CRIME W1
-	1	2.16	3.92	6.08	0.00
-	2	Control Beat/No Information Available			
-	3	0.53	3.27	3.80	0.00
-	4	0.23	0.64	0.87	0.00
-	5				

AMOUNT REQ	ORDER	DISC. TIME W2	CALL TIME W2	TOTAL HRS W2	CRIME W2
-	1	2.25	3.00	5.25	0.00
-	2	Control Beat/No Information Available			
-	3	0.35	1.67	2.02	0.00
-	4	0.26	0.94	1.20	0.00
-	5	0.37	0.89	1.27	0.00

AMOUNT REQ	ORDER	DISC. TIME W3	CALL TIME W3	TOTAL HRS W3	CRIME W3
10.00	1	1.56	3.75	5.30	0.00
10.00	2	Control Beat/No Information Available			
10.00	3	0.30	5.35	5.65	2.00
10.00	4	0.23	2.78	3.01	1.00
25.00	5	0.82	4.00	4.82	0.00

DEFINITIONS:

RA = Reporting Area, PO = Property Offenses, RB = Residential Burglaries, DP = Directed Patrol

AMOUNT REQ = Amount of attention requested (in hours) for the place or intersection by the Watch listed at the top of this report

DISC. TIME = Discretionary time (in hours) CALL TIME= (in hours) TOTAL HRS = Discretionary + Call Time

W1 = Watch 1 W2 = Watch 2 W3 = Watch 3

Control Condition

The control condition consisted of standard police responses in the beats that were allocated as controls. Accordingly, police continued to patrol these areas at the normal levels and would respond to calls for service originating in these areas as usual. The use of random assignment to allocate beats to treatment and control areas allows us to assume that there were no systematic differences in the characteristics or situations of the beat areas that would confound our experimental results. The use of crime trajectories as a blocking factor gives further confidence to the fair comparison between beats for which AVL information was available and beats for which AVL information was not available. We monitored intended deployment in the control sites as a means of assessing actual differences in patrol dosage allocated and received between the experimental and control locations.

Findings

As noted above, to assess the impact of AVL on police deployment and crime, we examined two ways in which knowledge about actual deployment might impact upon patrol. In the first case we were concerned with how knowledge about AVL might influence beat level deployment decisions. This was the level of random allocation of the study, and was the question that most concerned the Dallas Police Department when we designed our study. Accordingly, the first question in our study was whether the knowledge about deployment patterns in beats in a previous week affected the ability of the department to gain the level of patrol that was desired in the subsequent week. We also examined in this part of our study whether knowledge about AVL influenced the "expectations" of patrol of police Commanders, and whether there is any indication that crime rates were affected in the treatment as opposed to control conditions.

We also sought to answer another question that we thought was crucial in assessing the utility of AVL in allocating police patrol. At each weekly divisional Compstat meeting the Division Commander identified specific hot spots of crime. This approach is very consistent with the growing research evidence that effective and efficient policing will be enhanced by focusing on those specific places where crime is concentrated (Braga, 2007; Braga & Bond, 2008; Braga et al., 1999; Braga & Weisburd, 2010; National Research Council, 2004; Sherman &Weisburd, 1995; Sherman & Rogan, 1995; Weisburd, 2008). Accordingly, we assessed in our evaluation whether the beats with AVL information were able to more effectively bring police patrol to crime hot spots. We also examined whether Commanders' expectations of patrol in those places changed with this knowledge, and whether crime was impacted. Our findings are organized around the research questions we identified earlier in the report.

The Effects of AVL Knowledge on Beat Area Outcomes

The major benefit of a randomized design is that it allows us to establish a causal relationship between treatment and outcomes, and makes it unnecessary to take into account other confounding factors in analysis of outcomes (Boruch, 1997; Boruch et al., 2000; Weisburd, 2003). As we noted earlier, we decided at the outset to use a randomized block design for the study (Ariel & Farrington, 2010; Gill &Weisburd, In Press; Weisburd & Gill, In Progress; Weisburd & Taxman, 2000). In this case, we first identified four groups of beats ("blocks") using trajectory analysis. We then randomly allocated the beats within each block into an equal number of treatment and control conditions.

As noted above, this approach has two main benefits. First, it maximizes the comparability of the groups. Randomization allows the researcher to assume that there are no systematic differences between the groups. Nonetheless, when there is large variability in the case of key outcome measures, blocking before randomization will increase the equivalence of the observed groups. The trajectory analysis showed that there were distinct developmental trends in the crime data across beats. By randomly allocating within blocks, we minimize the possibility of chance differences on this factor in the study. But blocking also allows another benefit in this analysis. The addition of the blocking term generally leads to a more powerful statistical outcome, as the blocking term is expected to reduce the error sums of squares (which is used as the denominator in tests of statistical significance) without influencing the treatment sums of squares in the study (Gill &Weisburd, In Press; Weisburd & Gill, In Progress). The introduction of this term also adjusts for the loss of degrees of freedom associated with the introduction of restrictions on randomization caused by blocking.

We also test in our models for possible treatment by block interactions, since it may be the case that the treatment has different effects depending on the statistical block (divided in our study by type of crime trajectory) in which the beat is located. Following Fleiss (1986), we included the block by treatment interaction in our analysis models only if it reached statistical significance, as the term can add instability to the models estimated. Accordingly, our basic statistical model followed the following approach using a linear and additive design:

$$Outcome = B_0 + BTreatment + BTrajectoryAssignment + BTreatment*BTrajectoryAssignment$$

Our analysis is based on weekly assignments. This was consistent with the approach used in Dallas to assign patrol resources and reflected the weekly Compstat meeting organization of the department (see earlier on pp. 17-18). In analyzing our data we examine each week separately and also the cumulative figures for each beat across the 13 weeks of the study.

Research Question 1: Does knowledge about actual police patrol influence the time that police managers expect patrol cars to spend in patrol beats under their supervision?

Figure 9 shows the actual weekly "intended" patrol for the treatment and control conditions. Intended patrol is simply the amount of patrol that was assigned by Commanders in the division to specific beat areas each day added cumulatively over a week. In every week of the study the experimental beats had more patrol requested than the control beats. Remember that our randomization procedure allows us to assume that absent the treatment the two groups would be similar. By using a block randomization procedure, we further reinforced this assumption, by making sure that the groups were equivalent in terms of trajectories of crime before the experiment. Because of the skewed distribution of the data, we used logged intended patrol (base 10) as our outcome in assessing the statistical significance of the results.[17] For the overall experimental period, the difference is significant at the .001 level (see Table 1). The treatment beats averaged 939.61 hours of intended patrol per beat each

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[17] The results are also statistically significant when we analyze the raw totals, though the strength of the relationship is not as large.

week, while the control group averaged only 803.14 hours. The differences are also statistically significant in 13 of the 13 weeks of the experiment (see Table 2).

Figure 9: Average weekly hours of intended police presence in Treatment versus Control beats

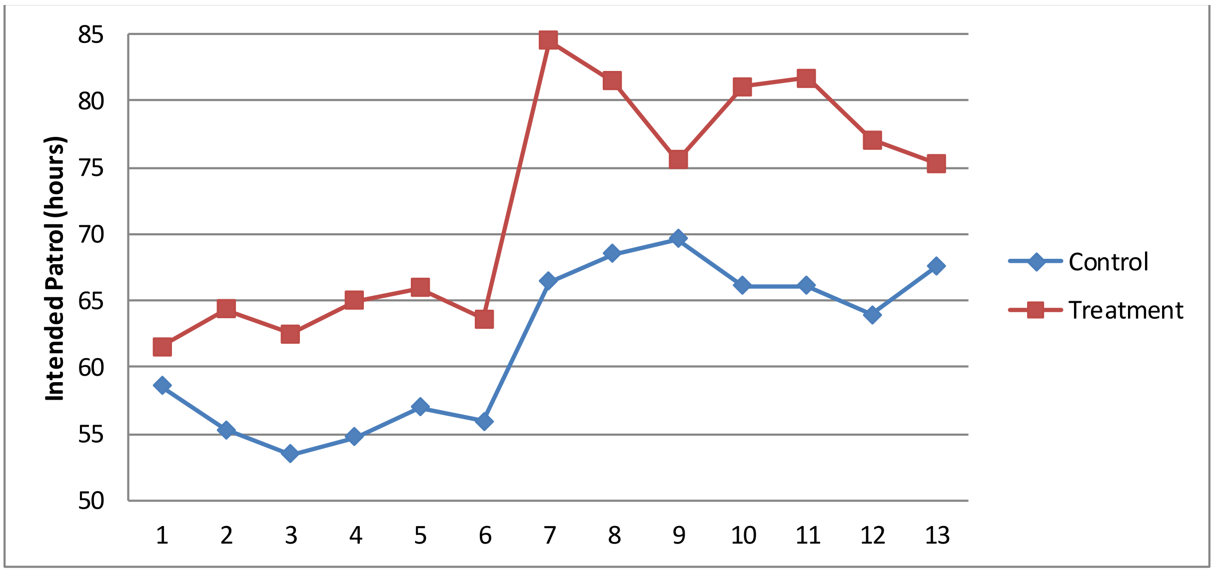


Table 1: Logged patrol intended by treatment and trajectory group[18]

Source of variation	Sum of Squares	*df*	*F*
Corrected Model	1.517[a]	7	7.443***
Intercept	1056.74	1	36281.41***
Traj	0.495	3	5.666***
Assign	0.42	1	14.406***
Traj * Assign Interaction	0.454	3	5.194**
Error	6.524	224	
Total	1968.08	232	

*p < .05; **p < .01; ***p < .001

[18] Summary tables of the linear models of patrol intended, patrol performed, and crime are depicted in the body of the report. Tables depicting the full model are provided in Appendix C.

Table 2: Patrol intended by week and treatment group

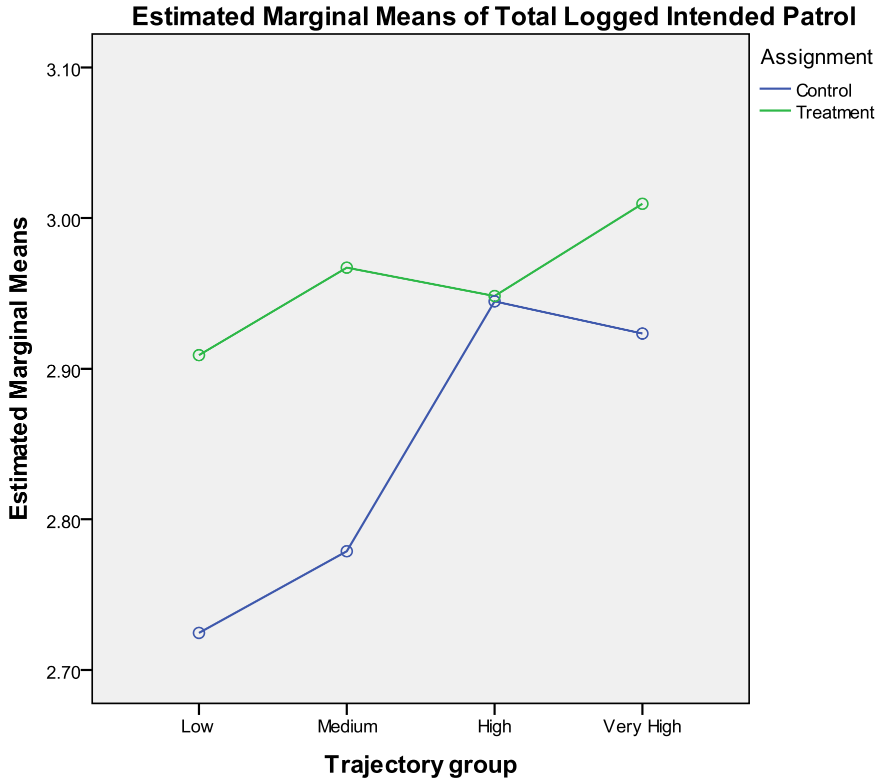
Week	Treatment#	Control	*F*
1	61.272	55.756	5.198*
2	63.609	53.798	15.022***
3	63.208	51.957	19.320***
4	64.438	52.998	16.292***
5	66.249	55.226	15.746***
6	63.843	63.892	8.220**
7	85.341	64.642	16.494***
8	82.714	66.277	12.699***
9	76.364	69.524	3.940*
10	82.718	63.111	15.424***
11	83.265	64.439	9.952**
12	78.851	62.612	7.725**
13	77.320	66.596	6.281*

*p < .05; **p < .01; ***p < .001

Actual hours of patrol are reported here. The F test is based on logged hours of patrol.

For this model the interaction term between treatment and block was statistically significant (Table 1). This means that the impact of treatment was different across the four trajectory crime patterns we identified in our data. Looking more closely we can see that in each trajectory group the treatment sites had more intended patrol than the control sites (see Figure 10). However, the difference was much smaller for the "high crime" trajectory grouping. Said another way, there was little difference between treatment beats and experimental beats that were part of the "high crime" trajectory group but significant differences for the other groups.

Figure 10: Logged intended patrol by treatment and trajectory group



Research Question 2: Does knowledge about actual police patrol influence the amount of patrol delivered in a beat area?

Accordingly, our first analysis shows that the AVL treatment impacted upon what Commanders "expected" in their beats. Overall, having access to AVL information led them to expect more patrol in the beats than the control condition. But did this request for more patrol actually lead to higher levels of patrol? On average, there is a slightly higher level of patrol achieved in the experimental beats than the control beats (see Figure 11). However, these differences are very small. Analyzing again the logged number of hours of patrol performed, the overall difference between the groups is not statistically significant (see Table 4).[19] Nor were any of the weekly comparisons statistically significant (see Table 5).[20]

Accordingly, our results show that the availability of AVL data led to Commanders expecting more patrol in their beats, but it did not lead to an increase in actual patrol levels. We will return to this finding in more detail in our discussion, but we think our findings are very important in that they suggest that AVL leads to expectations that patrol resources can be allocated with greater control by Commanders, but that is not achieved in practice.

[19] We also analyzed the data with the raw totals. The results were similar. The interaction term between treatment and block was not statistically significant.

[20] However, the amount of patrol achieved was greater than the intended amount for both the treatment and control beats. While this result may be seen as counter-intuitive, we think it develops from the nature of the information we provided commanders. We listed in the information sheets the total amount of actual patrol time, which included patrol time for patrol as well as units not under the control of patrol commanders. They were aware of this and likely took this into account. At the same time, we think that the critical information that led to higher requests for patrol in the experimental beats was the "free" time data provided. We suspect that the commanders saw from this that they had a good deal of free time, and wanted to utilize this. The reality is that they could not as we discuss later.

Figure 11: Average weekly hours of AVL measured police presence in Treatment versus Control beats

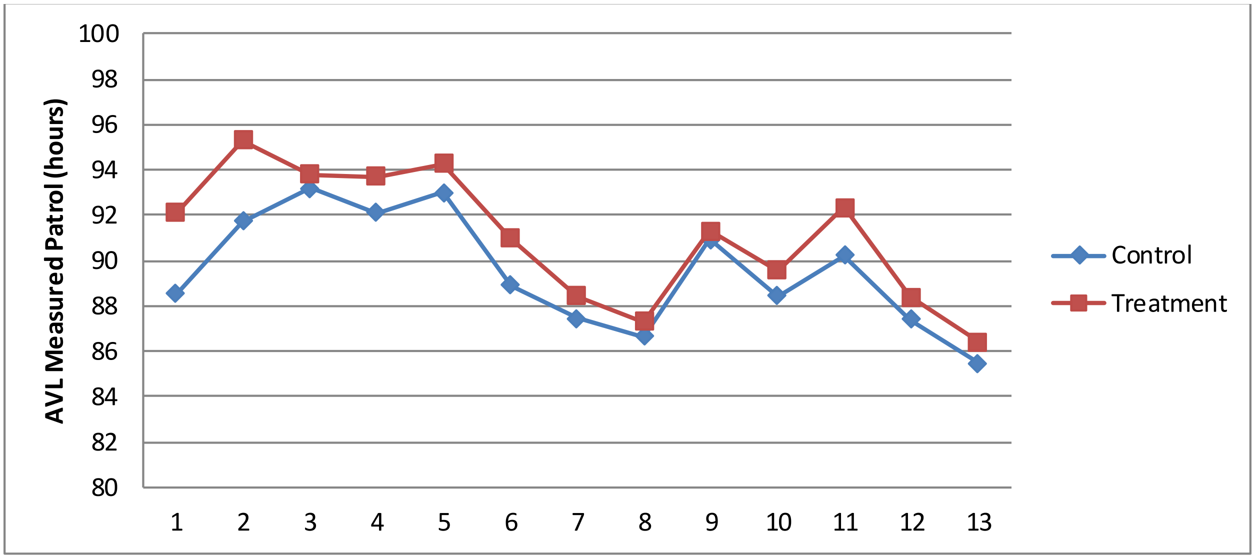


Table 4: Logged patrol performed between trajectory and treatment groups

Source of variation	Sum of Squares	Df	*F*
Corrected Model	2.080[a]	4	9.331***
Intercept	1142.637	1	20499.52***
Trajectory	2.08	3	12.441***
Assignment	0.001	1	0.014
Error	12.653	227	
Total	2079.329	232	

*p < .05; **p < .01; ***p < .001

Table 5: Weekly patrol performed by treatment group

Week	Treatment#	Control	*F*
1	103.34	99.094	0.074
2	107.316	103.04	0.118
3	106.2	104.93	0.049
4	105.2	102.97	0.037
5	106.113	104.18	0.006
6	102.664	99.982	0.040
7	100.22	98.729	0.002
8	99.053	97.799	0.030
9	103.966	102.95	0.010

10	100.815	99.070	0.089
11	103.553	100.77	0.077
12	100.069	98.543	0.000
13	97.409	95.864	0.097

*p < .05; **p < .01; ***p < .001

#Actual hours of patrol are reported. The F test is based on logged hours of patrol.

Research Question 3: Does knowledge about actual police patrol allow managers to gain greater consistency between the amounts of patrol that they request in any police beat with the actual amounts of patrol delivered?

While we do not find differences in actual patrol between the groups, it is possible that AVL knowledge affected the relationship between intended and actual patrol. For example, perhaps the treatment group, while not gaining additional patrol, showed a stronger correlation between the amount of patrol expected and the amount of patrol received. This hypothesis is also not supported by our data. Table 6 lists the correlation between actual and intended patrol for the treatment and control conditions across the 13 weeks of the experiment, and in summary, across the experiment using logged AVL data. To assess whether the consistency in the two groups was greater than would be expected by chance we used a statistical test developed by Paternoster and colleagues (1998).

It is clear overall that the correlations are relatively small, suggesting that there is a large gap in general between the amount of patrol requested and the amount actually achieved (see Table 6). But more important for our purposes, there is not a significantly higher relationship in the treatment group than the control group (see "overall" result). Of the weekly comparisons, only two are significant and in both of those the control group had a stronger correlation between intended and actual patrol than the treatment group. Overall, there is no evidence that AVL knowledge improved the fit between actual and intended patrol.

Table 6: Weekly correlation between actual and intended patrol by treatment group and week

	Control	Treatment	SE	Z
Overall	0.063	-0.043	0.094072	0.797592
1	0.114	0.059	0.094072	0.416641
2	0.044	-0.09	0.094072	1.00928
3	0.069	-0.076	0.094072	1.091843
4	0.16	-0.142	0.094072	2.287713*
5	-0.012	-0.086	0.094072	0.557828
6	0.031	-0.038	0.094072	0.518861
7	0.058	-0.145	0.094072	1.534106
8	0.115	-0.21	0.094072	2.47059*
9	0.073	-0.042	0.094072	0.865578
10	0.047	-0.075	0.094072	0.918352
11	0.08	-0.043	0.094072	0.926035
12	0.111	-0.003	0.094072	0.86035
13	0.051	0.0	0.094072	0.383682

*p<.05 **p<.01 ***p<.001

Research Question 4: Does knowledge about actual police patrol lead to crime reductions in the experimental beats?

Because we do not see any significant difference between the treatment and control groups in terms of actual police presence, we would not expect AVL to have an impact on crime. This is because the impact would be expected to come from the extra police patrol resources brought to the experimental beats because of the AVL treatment. Nonetheless, we examine the crime outcomes of the experiment. It is always possible that AVL influenced patrol allocations in some way that is not picked up by our data.

As expected, we do not find significant differences in crime over the study period (see Tables 7 and 8).[21] We use logged crime figures, as the distribution examined is very skewed.[22] Figure 12 shows that the two groups, as expected if there were randomization but no treatment effects, are very similar in terms of crime outcomes during the study each week of the study.

Table 7: Logged crime in by treatment and trajectory group

Source of variation	Sum of Squares	df	*F*
Corrected Model	3.511[a]	4	39.677***
Intercept	125.384	1	5666.976***
Traj	3.507	3	52.839***
Assign	0.001	1	0.049
Error	5.022	227	
Total	232.748	232	

*p < .05; **p < .01; ***p < .001

Table 8: Crime by treatment group and week

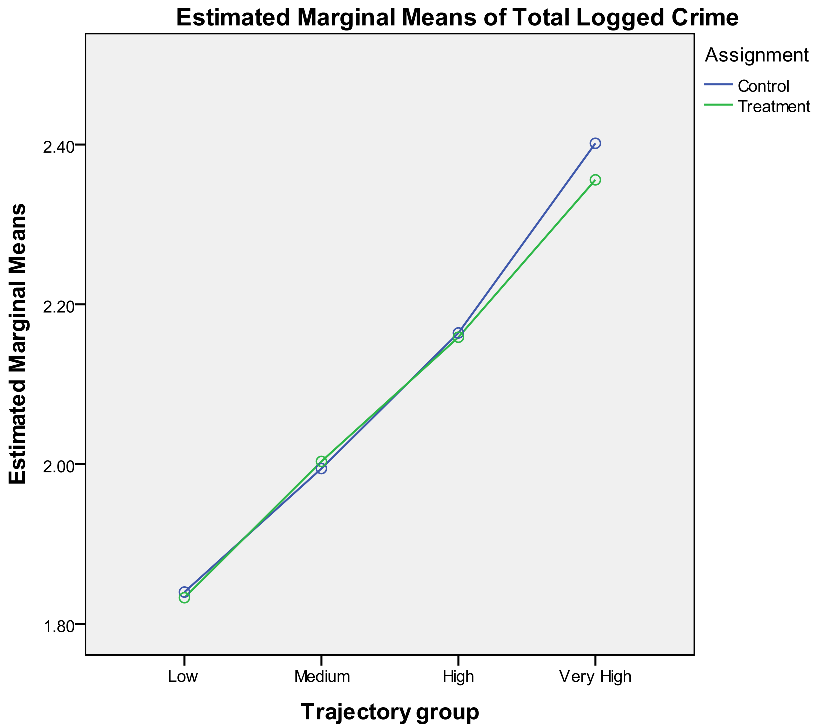
Week	Treatment#	Control	*F*
1	10.363	10.608	0.051
2	10.826	10.63	0.049
3	10.647	10.66	0.667
4	10.965	11.211	0.126
5	10.921	11.602	0.252
6	10.888	11.446	2.973
7	10.899	11.127	0.867
8	11.373	11.167	0.595
9	11.036	11.432	0.002
10	10.943	11.013	0.831
11	10.958	11.22	0.101
12	10.572	10.184	1.162
13	9.341	9.722	0.000

[21] We use crime data for the full week of observation (see earlier). Analyzing the data for the five day period we find similar results.

[22] We also analyzed the data using the raw figures. The results are similar. We show here the seven day comparisons (see earlier).

*p < .05; **p < .01; ***p < .001
#Actual numbers of crime are reported. The F test is based on logged counts of crime.

Figure 12: Logged crime by treatment and trajectory group



The Effects of AVL Knowledge on Hot Spots Policing

While AVL is not found in our study to help in achieving higher levels of deployment in beats (though it increased expectations of patrol in the experimental group), we also sought to examine whether it enabled Compstat Commanders to get more patrol to the specific places which they identified as crime hot spots. As noted earlier, during the experiment we asked the Commanders each week to identify up to five specific places where they wanted more intense patrol. We were able to collect valid data for 12 of the 13 weeks of the experiment, and identified 1,141 hot spots for this analysis:[23] 633 or 55% of these hot spots were in the experimental beats and 508 or 45% were in the control beats. The difference between the number of treatment and control hot spots must be interpreted cautiously. Because our data collection sheet only included values for up to five hot spots for each division for each week for each shift, it may be the case that in some of the divisional Compstat meetings more than five hot spots were identified but not captured by our data collection. Additionally, when larger areas were identified by Commanders, our approach was to divide up them into smaller hot spots after the data forms had been completed which means that there are sometimes more than five hot spots included in specific units.

In analyzing whether more patrol was brought to the experimental hot spots as opposed to the control condition hot spots, it is important to note that our unit of analysis is no longer the same as our randomization unit. There is the possibility of having more than one hot spot in each beat, and indeed the number of hot spots per division Compstat meeting per shift per week varies. At the same time, it remains the case that the design provides a credible comparison for the AVL treatment. Once a hot spot has been designated, the question becomes whether presence in a treatment beat condition has an impact on expected patrol, actual patrol or crime. If there is a bias in our analysis, we might expect it to be against the treatment condition, since as we have already seen there are a larger number of hot spots reported in the experimental condition, but the patrol resources may be assumed to be similar

[23] Both AVL and crime data were corrupted for the first two weeks of the experiment. The overall beat level statistics were not affected.

(since there are an equal number of experimental and control beats in each of the four blocks of cases).[24] Because the units of analysis are hot spots, we follow a simple experimental analysis for the following tables in which we compare the outcomes for the treatment and control condition, without including the blocking factor.

> Research Question 5: Does knowledge about actual police patrol influence the time that police managers expect patrol cars to spend in directed patrol areas in their beats?

Figure 12 shows the average patrol assigned by group by week for the treatment and control hot spots. The differences are not large and differ in direction from that of the beat analysis. The overall patrol assigned to treatment hot spots is slightly lower with 11.413 hours per week on average while that of control is 12.188 hours. However, the overall differences are not statistically significant (see Table 9).[25] We do not look at the significance of weekly differences between treatment and control groups in this and subsequent hot spots comparisons, as the numbers are relatively small and the samples vary in size week to week.

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[24] This estimate as noted earlier is also not certain because our reporting requirements only required up to five hot spots be identified. Nonetheless, we think it a reasonable assumption given the randomization approach.

[25] The distribution in this case was not skewed enough for us to transform the outcome measures. At the same time, we wanted to perform sensitivity analyses in which we examined only specific ranges of cases. When we examine patrol intended for only those hot spots with less than 40 hours, or 20 hours of patrol assigned the findings are similar.

Figure 13: Average patrol assigned by group and week for treatment and control hot spots

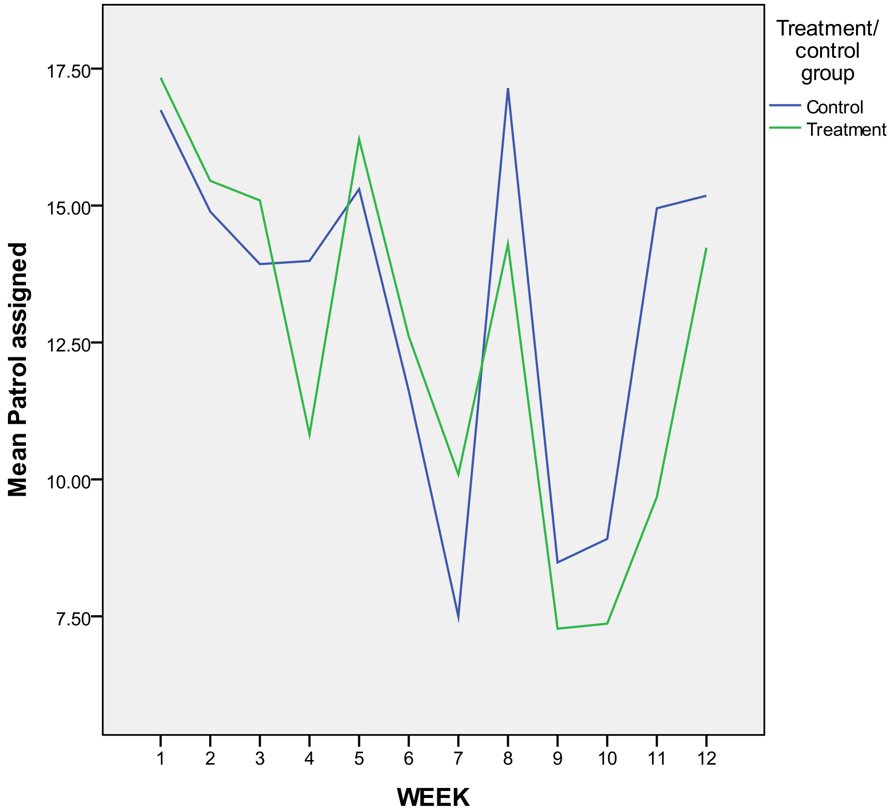

Table 9: Patrol assigned by treatment group

Week	Group	N	Mean	SD	T
12 week period	T	642	11.413	9.628	1.314
	C	517	12.188	10.399	

*p < .05; **p < .01; ***p < .001

Research Question 6: Does knowledge about actual police patrol influence the amount of actual patrol delivered in a hot spot area?

While our data do not show differences in expectations of Commanders, they do suggest that AVL leads to higher levels of actual patrol at crime hot spots (see Figure 9). Figure 13 shows that in only three weeks during the experiment did the control condition beats perform more patrol hours on average in the hot spots than the treatment condition beats, and in these three weeks the differences are relatively small. Overall, the treatment group hot spots received significantly more patrol during the study period (p<.01; see Table 10). On average treatment group hot spots received 4.7 hours of patrol per week while control hot spots received 3.7 hours.[26] Accordingly, the treatment group hot spots received on average almost 30% more patrol than the control group hot spots.

[26] The distribution was somewhat skewed with a cluster of values above 30 hours per week. We do not think that the number of such values was large enough to warrant logging the dependent variable. Nonetheless, a logged outcome measure for the observation period still yielded significant results.

Figure 14: Patrol performed by week for treatment and control hotspots

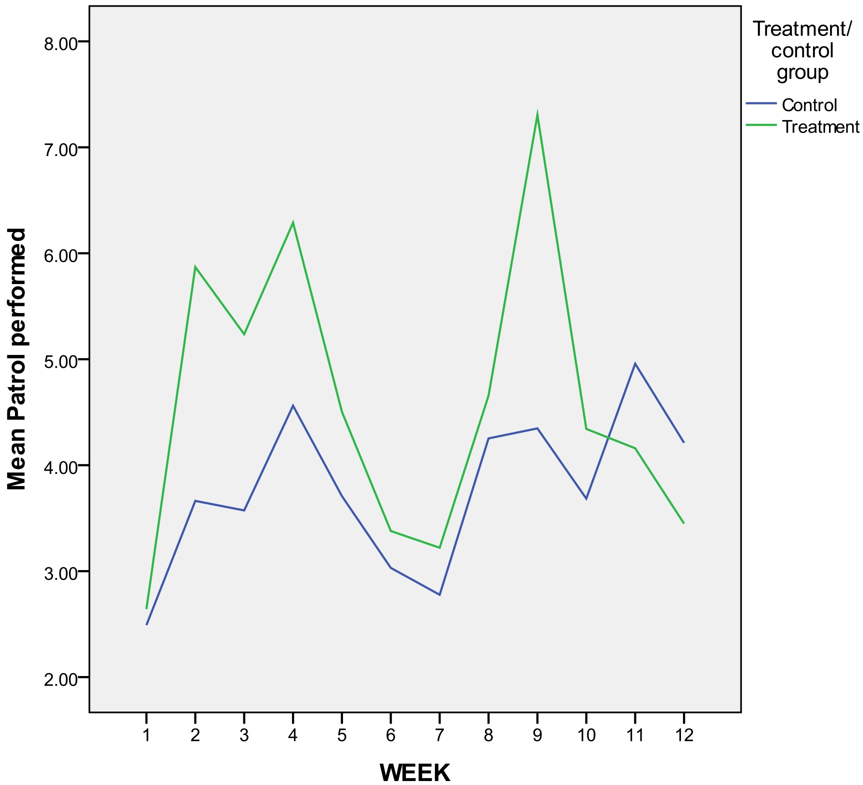

Table 10: Patrol performed by treatment group

Week	Group	N	Mean	SD	t
12 week period	T	633	4.711	6.969	-2.883**
	C	508	3.696	4.228	

*p < .05; **p < .01; ***p < .001

Research Question 7: Does knowledge about actual police patrol allow managers to gain greater consistency between the amount of patrol that they request in any directed patrol area and the actual amount of patrol delivered?

Given our finding regarding the intensity of patrol at hot spots, it is perhaps surprising that we do not find a significant relationship between AVL knowledge and consistency between the hours of patrol intended and those delivered. The correlations are larger than in the previous analysis, and again the control group has a slightly higher correlation. But the difference of correlations statistic is not statistically significant, suggesting again there is not a meaningful difference between treatment and control in terms of the relationship between intended and actual patrol deployment. In both groups the overall consistency appears modest.

Table 11: Correlation of patrol performed and crime in treatment and control groups by week

	Control	Treatment	SE	Z
Spearman correlation: 12 weeks	0.283	0.204	0.029	-1.41837

*p<.05 *p<.01 *p<.001

Research Question 8: Does knowledge about actual police patrol at hot spots lead to crime reductions in the directed patrol areas in the experimental beats as contrasted with the control beats?

Our finding that the actual patrol in hot spots was influenced by AVL information leads to the question of whether the increase in patrol in these areas led to a decrease in crime. Our statistics here it should be noted are limited to the same week in which the patrol resources were brought. Accordingly, we measure whether on average the treatment group hot spots showed lower crime rates for the specific weeks that they were designated as crime hot spots.[27] The overall influence of AVL information on crime shows that there is a significant treatment impact (p<.001; see Table 11) with the treatment condition evidencing about a 20 percent relative *decline* in crime. The absolute value for the hot spots in the treatment condition is 1.98 events per hot spot per week, while that for the control is 2.42 events per hot spot per week. Figure 14 suggests that this relationship is complex looking week to week in the

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[27] The analysis is done on the full seven day week. Using the five day observation period (see earlier) the findings are similar.

experiment, though overall when there are larger differences they are in favor of the experimental condition. These results are highly significant suggesting that on average crime was lower in the treatment as contrasted with the control condition. They are also consistent with previous research on the effectiveness of hot spots policing (Braga, 2007; Braga & Weisburd, 2010; NRC, 2004; Weisburd, 2008) and our prior findings regarding the higher average level of patrol presence found in the treatment hot spots.

Figure 15: Crime by treatment group and week

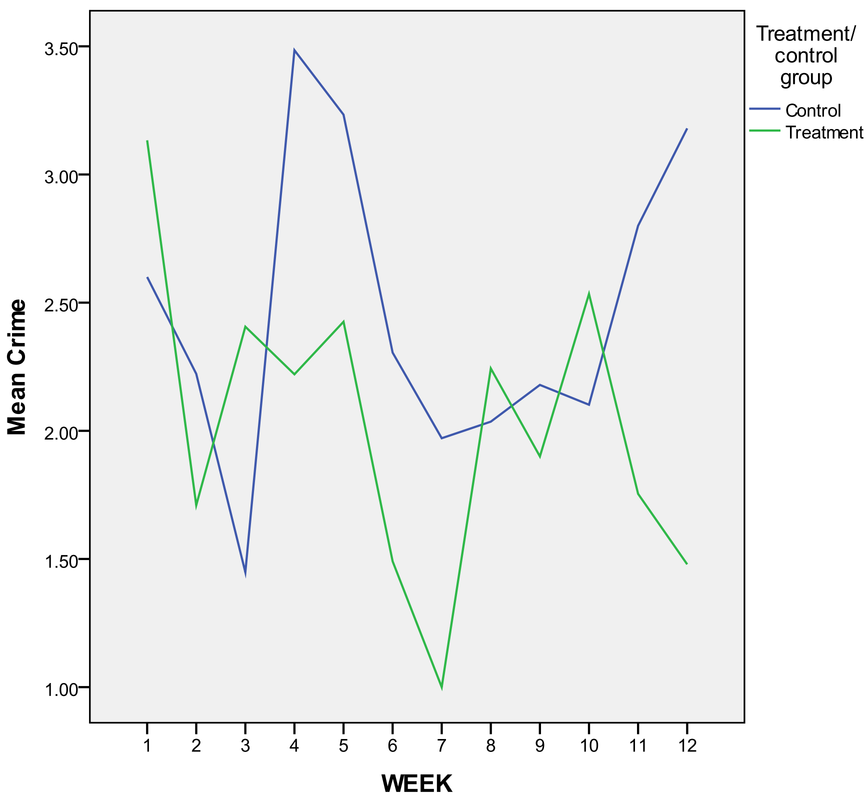

Table 12: Crime by treatment group

Week	Group	N	Mean	SD	t
12 week period	T	642	1.978	2.391	2.965**
	C	517	2.420	2.671	

*p < .05; **p < .01; ***p < .001

DISCUSSION

Our findings regarding the influence of AVL knowledge on allocations of police patrol, and its impacts on crime are intriguing. We find overall, that AVL knowledge led Compstat Commanders in Dallas to increase the amount of patrol that they expected in experimental beats relative to the control beats. But that increase in expectations did not lead to a significant increase in the actual allocation of patrol in the treatment as compared to the control condition. Not surprisingly, we did not find any crime prevention benefits at the beat level for the treatment condition. This would imply that AVL knowledge, at least in the way that it was applied in Dallas, does not lead to any improvement in patrol allocations. But when we examine hot spots, we find precisely the opposite impact of AVL. It did not affect the overall number of hours assigned. But it did increase the amount of patrol actually performed (despite the larger number of hot spots assigned) in the treatment condition. And this increase in patrol appears to have led to a decrease in crime in the treatment hot spots.

How can we explain these markedly different results found at different geographic levels of policing? And what insights do our findings bring to the use of AVL in the future in police agencies? This is what we focus on in the following discussion of our findings. We think they make very good sense given what we know about policing, and that despite limitations of our study, which we will discuss before concluding, our findings lead to strong policy conclusions.

Why does AVL increase expectations of patrol in the beat level, but not have any observed impact on the amount of patrol performed? With access to the actual patrol figures, the AVL beat Commanders clearly felt that they could assign more hours of patrol. We suspect that having seen the actual deployment figures they wanted to increase the number of hours overall spent in particular beats under their command.[28] The AVL data includes fields identifying "free (discretionary) time" versus "time on call" for patrol cars, and this data was available to the Commanders on the forms that we gave them. If one looks simply at the number of "free hours" of patrol time, then the numbers observed can be very large. For example, each wee k the treatment group had on average more than 800 hours of "free time." Perhaps the Commanders in the experimental beats saw such figures and assumed that they "should" have more time to allocate in their beats. In contrast, in the control condition no information on patrol levels achieved was provided, the Commanders simply "assigned as usual" their officers.

But the reality is that when one considers the amount of "free time" versus total patrol time, that there is a ratio of about 3-1 hours. Most patrol time, about 75%, is assigned by

[28] Knowing the large impact of calls for service on patrol activity, it is possible the beat commanders took that into account as they made deployments. Since they knew the figures were inflated by cross-beat travel to answer calls and return to the home beat, they may have adapted and decided that to get more free time in a beat they had to ask for more time overall to be spent there.

dispatchers. In this reality "field operations" priorities are actually a small part of the overall patrol model. Indeed, DPD Commanders we spoke to often stated that they do not have the primary control over where their officers spend time; it is controlled by 911 calls for service received.

One problem in interpreting our data is that in both the treatment and control conditions, the beats received on average more patrol than was assigned. The treatment group on average had much higher expectations but both groups still exceeded their expectations in actual patrol time on average across the experimental conditions. But it still might be argued, that given the increase in expectations, there still should have been a relative increase in patrol in the experimental beats. It might be argued in turn, that they should have been able to influence actual patrol-- because on average our data suggest that the police had many hours during a shift which were not devoted toward emergency responses (see also Famega, et al., 2005; Mastrofski, et al., 1998). However, the free time data may be misleading. It is important to remember that this "down" time includes not only bureaucratic tasks such as status report updates via mobile display terminals (MDTs) and breaks, but also driving back to the originally assigned beat after a cross beat dispatch. We suspect that in Dallas, as in other cities where police patrol large geographies, such time can be substantial and in reality the officers may not have as much free time as has often been assumed.

But this raises the question: why could Commanders bring greater resources to crime hot spots? Moreover, why did the Commanders not expect more hours at treatment hot spots than control hot spots if they expected more resources at treatment beats but not control beats?

The answer to this latter question can be found perhaps in the more specific nature of hot spots policing allocations. Beat areas are large geographies, and specifying how much patrol should be given to each is difficult to focus upon in very specific terms. Of course, high crime beats would be assigned more patrol than low crime beats. But the boundaries of such assignment numbers would be expected to be imprecise. However, police attention to specific places, or hot spots, is a much more concrete focus for Commanders, and we suspect that in coming to a decision about how much patrol to allocate they have clearer expectations that are not likely to be influenced simply by a desire to gain more patrol. The treatment for any specific hot spot is in this sense independent of knowledge about police patrol brought by AVL data.

In considering why hot spots in the treatment areas received more police patrol than those in the control condition, it is important to note that in both groups the number of hours performed was much lower than the number of hours expected. So, in one sense the experimental hot spot assignments reflected the success of the experiment in bringing more time (though less than allocated) to the experimental sites.

But, if we have already argued that it is difficult for police Commanders to influence actual police patrol at the beat level, why are they able to do that at the hot spot level? The answer to this question, we believe, lies in the nature of what is being requested by Commanders. In the case of beat level allocations, when the Commanders ask for more time they are asking patrol officers to increase the actual amount of time that they devote to preventive patrol activities in a beat. As we have already noted, it simply may be that in departments like the DPD the patrol officers simply cannot "create" more time in their shifts. In the case of hot spots allocations, the request of the Commanders means something different to patrol officers. Specifically, that the officers are being asked to focus the preventive patrol time they have to specific, manageably small places. In this sense, they are asking the officers to reallocate their time, not create new time. They are being asked to focus their patrol activities, not to find additional patrol time.

This indeed fits the logic, as we noted earlier, for hot spots policing more generally. One of the major findings of the Minneapolis Hot Spots Patrol Experiment (Sherman & Weisburd, 1995) was that police could be effective in reducing crime if they focused their resources on crime hot spots. Sherman and Weisburd argued that it was wasteful to spread preventive patrol across a city if crime was concentrated at a small number of places. Moreover, focusing police resources on specific places would allow the police to bring higher dosages of patrol to those places (Weisburd, 2008; Weisburd & Telep, 2010). This experiment shows that AVL information allows Commanders to increase the concentration of ordinary patrol resources at crime hot spots by reallocating patrol time.

Finding a crime prevention effect at the hot spots simply follows these findings and the literature on the effectiveness of hot spots policing (Braga & Weisburd, 2010; NRC, 2004; Weisburd, 2008). Our data show that knowledge about AVL leads to lower crime rates overall in the hot spot areas. There is nothing surprising about these results, given our finding that AVL knowledge increases patrol hours at crime hot spots. There is now a strong experimental and quasi-experimental literature that shows that increasing police patrol at hot spots will lead to decreases in crime (Braga, 2007, Braga, Papachristos, & Hureau, Under review; Weisburd & Eck, 2004). This was first established in the Minneapolis Hot Spots Patrol Experiment (Sherman

&Weisburd, 1995), and it has been replicated in 19 studies using different methods of patrol since that time (Braga et al., Under review). What is new here is that the introduction of AVL can help the police to more efficiently and effectively increase police patrol at crime hot spots. This is an important finding, especially in an era when it is unlikely that police resources will be increased. Our study suggests that with existing resources the use of AVL can increase patrol time at hot spots and through such increases in patrol reduce crime.

Limitations

While we think that our findings are significant and can be used to draw strong policy implications, we think it important to note specific limitations of our study. While we use an experimental design which allows us to draw causal conclusions, our study period was relatively short. We think that 13 weeks for the beat experiment was long enough to observe effects, and this is reinforced by the significant findings observed. Nonetheless, the effects of AVL may strengthen or decline over longer periods of time and that should be examined in subsequent studies.

Perhaps most important in terms of the treatment itself, while the Dallas Police Department utilized AVL information in our experiment, they did not allow such information to be used as a supervision mechanism for individual officers. Accordingly, while Commanders could see how much patrol each beat or hot spot received, they could not link that patrol time to specific cars. It may be that the impact of AVL knowledge would be much greater if such information was available to Commanders. Indeed, it may be that AVL influence would also be salient for actual patrol time in beats if the Commanders could hold specific cars and officers accountable for specific patrol time on a daily basis. But we suspect that Dallas is not alone in being reticent to utilize such information. Police officers and unions have objected to the use of AVL data for supervisory mechanisms from the outset (Manning, 1992a, 1992b; Sorensen, 1998).

Finally, we want to reiterate that our analysis of hot spots is not fully consistent with our experimental design. Ideally, one would want to allocate hot spots to experimental and control conditions, and not, as we have done, examine hot spots within experimental and control beats. At the same time, police allocation of resources in Dallas as in many other police agencies is carried out at the beat level. Trying to randomly allocate AVL knowledge at the hot spot level would likely have been impractical in terms of implementation of our study.

CONCLUSIONS

The Dallas AVL Experiment provides important new data for our understanding of how AVL technologies can be used to maximize patrol in police agencies. Our data suggest that at least in cities like Dallas with large geographies and a 'first car available' dispatch philosophy, AVL information will not aid patrol allocations in large geographic areas. AVL in our study led to increased expectations for patrol at the beat level, but no significant differences in actual patrol levels. Not surprisingly, our study shows no significant impact of AVL knowledge on beat level crime rates.

Despite the sobering findings in our study regarding the use of AVL as a beat level management tool, our study suggests that AVL knowledge is a promising tool for enhancing hot spots policing approaches. Expectations for patrol hours in hot spots were not affected by the experimental conditions. However, AVL information did lead to significantly higher hours of patrol at the hot spots identified. AVL in this context can be an effective tool for enhancing hot spots policing approaches. Moreover, this increased patrol at hot spots was found to lead to lower levels of crime in the treatment areas.

These findings overall provide important guidance for police agencies. On one hand, they should be cautious in employing AVL as a management tool for large area patrol deployment. On the other, AVL can be an effective tool for enhancing hot spots policing approaches. Given the very strong empirical findings for the effectiveness of hot spots policing (Braga, 2007; Braga et al., Under review; Weisburd & Eck, 2004) and the findings of this study, a policy utilizing AVL to enhance directed patrol to hot spots areas appears particularly promising.

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DISSEMINATION OF RESEARCH FINDINGS

All project findings both quantitative and qualitative have been compiled into appropriate products for the purposes of informing the field through dissemination. The products developed and dissemination strategies for the knowledge gained are presented below:

PROJECT DELIVERABLES

1. ***Methodology Guide:*** This guide presents the various sets of methodologies used to process and analyzing AVL data to inform patrol deployment strategies. It provides step-by-step instructions

2. ***Phase 1 Report:*** This report presents our findings from phase one.

3. ***Scientific Article(s)***: This article describes, in detail, the research that was conducted, findings, and implications to the field. The article will be submitted to peer-reviewed criminal justice journals.

4. ***Practitioner Article:*** This article will be written for a police audience and submitted to a professional publication such as The Police Chief, FBI Law Enforcement Bulletin, and/or a GPS publication for law enforcement.

5. ***Final Evaluation Report:*** This report summarizes our evaluation of AVL technologies in the Dallas Police Department.

Each of our deliverables will be posted on the Police Foundation website. The site receives over 1,000,000 hits per year. The research team has presented interim findings from the research at the 2008 NIJ Research and Evaluation Conference in Washington, DC, the 2008 American Society of Criminology meeting in St. Louis, the 2009 International Association of Crime Analysts meeting in Scottsdale, AZ. The authors are willing to prepare a "Research in Brief." Finally, once the review process is complete we will provide a notification of our research results through the use of several relevant law enforcement email list serves (International Association of Crime Analysts, CrimeMap, and LEANALYST).

Appendix A: Trajectory Analysis Model Selection and Diagnostic Statistics

There are various decisions to be made before determining the final model : type of the model (Zero Inflated Poisson [ZIP], Censored Normal [CNORM], or Poisson), order of the model, and number of groups. Since our data have a significant proportion of beats with zero crime throughout the 52 weeks of the year, a Zero Inflated Poisson (ZIP) was chosen to take into account intermittency. To determine the order of the model, we tested all the models as linear, quadratic, and cubic form to examine which works the best to suit our data. The results show that the quadratic form of model fits best.

A key decision in these analyses is to decide on the number of trajectory groups. We followed the exhaustive approach detailed in Nagin (2005). That is, we tested for all possible combinations of number of groups and polynomial order of each trajectory. Specifically, we began our modeling exercise by fitting the data to a two trajectory group intercept-only model. We then fit the data to three trajectories and compared this fit with the two group solution. When the three group model proved better than the two group model, we then estimated the four group model and compared it to the three group solution. We continued adding groups all the way up to nine, but the improvement in BIC stopped at four groups. The same process was repeated for linear, quadratic models, and cubic models. When we went beyond nine groups, the model became extremely unstable, and thus, we did not think adding more groups would provide any valuable information.

The decision making process of determining the final trajectory model includes a degree of choices that are not determined by any absolute criteria. We first evaluated the trajectory results using the Bayesian information criterion (BIC) to determine the optimal number of groups in an analysis: BIC = log(L) – 0.5*log(n)*(k); where "L" is the value of the model's maximized likelihood estimates, "n" is the sample size, and "k" is the number of parameters estimated in the given model. Because more complex models will generally improve the fit of a given analysis, the BIC encourages a parsimonious solution by penalizing models that increase the number of groups unless they substantially improve fit. The final model selected is the quadratic ZIP model with four trajectory groups (BIC = -33888.45).

In addition to the BIC, trajectory analysis requires researchers to also consider posterior probabilities of group assignment, odds of correct classification, estimated group probabilities, and whether meaningful groups are revealed (Nagin, 2005). In this study, the minimum average within-group posterior probability for the majority of groups is .996 (for trajectory groups 1-3). In terms of the odds of correct classification (OCC), the following table shows that the lowest value is 335.507 and the majority have OCC values over 1,000 (Table AA1.1). Nagin (2005: 88) suggests that when average posterior probability is higher than 0.7 and OCC values are higher than 5, the group assignment represents a high level of accuracy. Judging by these standards, the four group ZIP model performs satisfactorily in classifying the 234 police beats into separate trajectories.[29]

Table AA.1: Odds of Correct Classification by Trajectory

Trajectory Group	*# of Beats*	*% of Total Beats*	*Avg. Posterior Prob.*	*Odds Correct Classification*
1	23	9.8	0.996	2291.816327
2	94	40.3	0.999	1479.908189
3	100	42.6	0.996	335.5070423
4	17	7.3	1.000	+∞

[29] The trajectory analysis was conducted with all 234 beats defined by the DPD. Two beats were subsequently dropped from the analysis because they were dominated by water bodies. Both beats were in Trajectory Group 1.

Appendix B: Data collection and Reporting

This section provides a detailed overview about the development of the project reports including important background information, an in-depth description about the project reports, and the comprehensive reporting process routinized during the experimental phase of the study which was conducted from March 9th, 2010 through June 7th, 2010.

Background Information

One of the primary objectives that had to be addressed before beginning the experimental phase was a decision about the geographic unit of analyses to use as the basis for both analysis and reporting purposes. Based on preliminary discussions between the research team and DPD's command staff, the main unit of analysis agreed upon was the police reporting area (PRA). However, after further discussions about DPD's current deployment operations a collective decision was made that the beat level would be the best unit of analysis. As a result, data and information in the reports developed for the project were reflected at the beat level. More importantly, to maintain methodological integrity these reports only contained information related to the treatment beats.

Project Reports

Another key objective addressed during Phase Two was the types of reports to use during the experimental period. After several discussions between members of the research team, input from DPD command staff, and other key staff members, we agreed on the following four project forms: 1) Crime and Presence Matrix Form, 2) Deployment Tracking Report, 3)

Compstat Target Form, and 4) Compstat Feedback Report. These reports were provided every Monday night during the experimental period so they could be utilized operationally at each division's Compstat meeting which were held every Tuesday morning department-wide. Below is a detailed description of the information provided in each report.

A. Crime and Presence Matrix Report – this report provides information on which category each experimental treatment beat[30] falls in for a specific division and watch (i.e., shift) based on the level of crime and police presence from the previous five day reporting period (Wednesday – Sunday). This report is divided into nine grids each representing a combination of a certain level of crime and police presence (e.g., low crime/high presence, medium crime/low presence). To determine the appropriate grid for each treatment beat in our study we utilized the information provided by DPD in Excel format and examined the amount of time attributed to each beat along with the number of crimes that occurred in each beat over the five day reporting period. This five day period was based primarily upon operational factors. Specifically, the fact that DPD's divisional Compstat meetings occurred every Tuesday. Thus, we wanted to make sure that this and other reports reflected DPD's existing operations. SPSS was used to establish the low, medium, and high thresholds for each watch. After establishing the thresholds, each treatment beat was placed in a grid based on their respective combination level (see Weisburd, Groff, Jones and Amendola, 2012).

B. The Deployment Module – this is a web-based intranet (only accessible by department personnel) application developed to obtain information about planned allocation of resources (i.e., cars) for each watch (including 4th and 5th) during the experimental period (see Figure 2). The main purpose of this module was to try to capture real operational figures or "deployment estimates" about how each division planned to allocate their elements/patrol cars during each shift on a daily basis. This information was later quantified and used to inform the Deployment Tracking Report described in the next section. The module was developed as a collaborative effort between the Police Foundation research team and DPD's Information Technology Division.

[30] The treatment beats were the same for each watch (shift) within the same division. For example, if beats 112, 116, 125, and 135 are selected as the treatment beats for Central Division, they are the same treatment beats for all watches associated with the Central Division.

C. Deployment Tracking Report (DTR) – this report provides information about planned "element" (i.e., patrol car) allocation and actual police presence for the treatment beats for each division and watch (see Figure 6). Specifically, this report provides a list of the randomly selected treatment beats for each of DPD's divisions, the total hours allocated, actual call time, and actual discretionary time. The figures provided in the total hours allocated were derived from the web-based deployment module. The actual call and discretionary time figures were derived from the Excel spreadsheet provided by DPD via use of the programming code described earlier in the report.

Once the Division Commanders and/or other designated personnel received this form they were asked to review it and decide if any changes in police coverage needed to be made for the subsequent week regarding police patrol presence. Next, they would indicate their decision by marking an "X" in one of the following options: 1) no change required, 2) increase coverage, or 3) decrease coverage. Once this form was completed for each watch or shift it was returned back via e-mail or fax to the project director.

D. Compstat Target Form – this was a blank form provided to the department that requested a list of the top places or intersections of interest (no more than five total allowed) that each division and each watch were planning to focus on each week based on crime activity and other department priorities (see Figure 3). These forms were collected for all five watches, however 4th and 5th watch entries were collapsed into whichever watch they selected as their primary watch in terms of command.[31] The purpose of this form was to get both a qualitative and quantitative understanding of how much time the department wanted to spend on each of these places or intersections they listed, the type of problem(s) occurring, and the type of attention (i.e., surveillance, directed patrol, traffic enforcement) planned to address the problem(s). The forms were usually completed by either the Division Commanders, Admin Lieutenants, or other designated personnel.

E. Compstat Feedback Report - this report provides feedback regarding the amount police presence activity at certain places or intersections vs. amount actually received at those places or intersection. This report is based upon the specific areas of interest listed on the weekly Compstat Target Form (see Weisburd, Groff, Jones and Amendola, 2012).

[31] In most cases the 4th watch reported to the 3rd watch commander staff so the designated officer would have selected the 3rd watch option on the target form they submitted. Other 4th watches reported primarily to the 1st watch command staff, thus the designated officer would have selected the 1st watch option on the target form.

The report provided information for places or intersections that were located in treatment beats only. In addition, the report shows the beats where the place or intersection is located, corresponding grid ID, type of problem(s), type of attention planned, the amount of attention requested by each watch, number of crimes that occurred, and how much attention received which was also broken down by discretionary time, call time, and total hours. The grid ID field was used to help identify the proper beat location during the mapping and geocoding process that is described in more detail in the next section.

ORGANIZATIONAL STRATEGY

A key strategy in implementing these reports within weekly operations of DPD was developing an organizational strategy in which the reports could be processed in a systematic manner. To maintain optimal operational efficiency in the processing of these four reports there were a number of tasks that had to be completed by the research team. These tasks were divided into two main areas. The first series of tasks involved establishing an organized soft (computer-based) filing structure and a systematic reporting structure. The tasks required the creation of the following:

a. a separate primary folder for each report
b. a weekly subfolder for each report (a folder for each week of the experimental phase)
c. folders for data dumps received from DPD
d. folders for data dumps received from the Information Technology Division
e. pre-formatted forms for each weekly subfolder for each of the forms and reports and each primary watch (i.e., updating date fields, watch numbers, etc.).

In addition to the computerized filing structure, we established a hard (paper-based) filing structure to serve as a secondary organizational mechanism and as a reference base throughout the project period for the four reports and other key project components. This structure involved creating the following:

a. a weekly Compstat Target Form folder and checklist
b. individual divisional binders to maintain hard copies of reports

c. a data entry checklist to track input in the deployment module
d. a weekly report checklist for the divisional binders

Each division was provided with a memorandum about the project goals and objectives as well as a project calendar which outlined the weekly process throughout the entire experimental period including: 1) the designated days when the four reports would be delivered, 2) designated data entry days (which were everyday during the experimental period), and 3) the designated days when certain reports were expected to be completed and returned to the project director. The weekly process was recurring and remained static throughout the experimental period.

THE REPORTING PROCESS

Each day, designated personnel for each watch within every division, typically the station sergeants, were tasked with completing the online deployment module which provided us with an idea about how many elements or cars were supposed to be assigned during their particular watch and to which beat(s). For example, if the supervisor planned for element/car #517 to be assigned to only Beat 114 during a particular watch or shift, they would enter in a "1" in the application next to this beat number. However, if they were short staffed, which in most cases they were, and they had to spread that particular element/car coverage across two beats then they would enter 0.5 in Beat 114 and 0.5 in Beat 115 (the other assigned beat). This information was collected for each beat for *all five* watches from all seven divisions. Calculating the total amount of time per beat for the primary watches was straightforward. For the three primary watches, we simply took the final element value for each beat over the five day reporting period and multiplied it by six.[32] However, to calculate the total patrol time per beat for 4th and 5th watch we devised specific rules to apply due to their overlapping time structures (see Figure A.1) and had to perform several additional manipulations using Excel.

Figure A.1 DPD Watch Hours

DPD Watch Hours		
1st Watch 12am – 8am	**2nd Watch** 8am – 4pm	**3rd Watch** 4pm – 12am
Watch 4am		**4th -** 6pm -
	5th Watch 10am – 6pm	

Two trainings (with the assistance of DPD's Information Technology Division) on the use of the web-based deployment application were provided by the project director to all designated DPD personnel. The trainings were scheduled to provide the following: 1) background and importance of the study, 2) to answer questions about the application, 3) to emphasize the importance of designated personnel participation, and 4) to maintain the integrity of the overall study.

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[32] The multiplier of six was used instead of eight because the actual time that an officer spends on patrol in a normal eight-hour shift is realistically closer to six because of other work-related duties including getting dressed, roll call, meal break, etc.

The reporting process revolved around a specific weekly reporting cycle which was Wednesday through Sunday. Every Monday morning, information captured by the deployment module based on the weekly reporting cycle was extrapolated by DPD's Information Technology Division and e-mailed to the project director (via an Excel file). This table was then manipulated to create total figures for the three main watches by beat per division. In addition, each Monday DPD provided an Excel table for each watch based on AVL activity covering the same weekly reporting cycle which included information about call time, discretionary time, number of crimes that occurred, and treatment/control designation for each beat. Both the deployment data and the AVL activity data in this table were used to create the DTR form. The DTR is an Excel-based form created for each division that includes three tabs where information can be entered seamlessly for each of the three main watches. The form only contains information related to the treatment beats. Specifically, we used the total hours calculated from the deployment information to complete the column designated as total hours allocated. We used the AVL activity data to complete the actual call time, actual discretionary time, and total actual columns. After the DTR forms were completed for all divisions, cross checks of all the spreadsheets were conducted by project staff to check for any gross errors and to maintain data integrity.

As mentioned previously, the information on the Crime and Presence Matrix Form was based on work performed using Excel and SPSS. First, we conducted a conversion (from minutes to hours) for each watch in the Excel-based AVL data file provided by DPD to obtain the total amount of hours (police presence) allotted to each beat for each main watch. Next, we broke the file into three separate files, one for each watch, and resaved them. Fourth, we opened each new watch file and ran frequencies on the total crime and total time to identify the low, medium, and high ranges for each watch based on the data for that week. Fifth, we referenced the original file (after sorting records by treatment and control beats) to identify which grid each treatment beat belonged to for each division. Finally, after all Matrix forms were completed for each division, cross-checks of all the forms were conducted by project staff.

The reporting process typically involved four to five project staff and averaged between 10-14 hours to complete depending on problems encountered during processing, errors or mistakes found on reports, formatting issues, etc. The most rigorous part of the reporting process was creating the Compstat Feedback Form which required meticulous rematching time due to many of the complex areas (i.e., block ranges) that were listed in the dataset.

Once a final cross check was completed on the reports they were e-mailed by the project director directly to the Division Commanders as well as several of the administrative lieutenants who were heavily involved in the report/feedback process. To minimize division confusion, we used a color-coded method for each divisional report and tried to keep each division's watch information to one page per report as much as possible. For example, all reports created for Central Division used a green color coding scheme while all reports created for Southwest Divisions used a purple color coding scheme. The DTR report included only three total pages or one page per primary watch. This was the same strategy for the other reports as well. Occasionally, the Compstat Feedback Reports were two pages per watch for some divisions.

Lastly, to promote further data entry compliance with the requested returned forms, each week we provided the division Commanders with a department-wide checklist that showed which watches were delinquent, if any, on daily entry duties (see Figure A.2). We also conducted daily audits of our divisional folders each week to ensure that we received the requested DTR forms and Compstat Target Forms for the upcoming week (see Figure A.3). If we identified missing forms or information for any division we immediately sent out reminders and requests to the appropriate point of contact.

Figure A.2: Sample Divisional Checklist

Web-Based Deployment Application:
Daily Input Checklist by Division and Watch
Week 3: March 22-28, 2010

	3/22/2010			3/23/2010			3/24/2010			3/25/2010			3/26/2010			3/27/2010			3/28/2010		
Division	W1	W2	W3	W1	W2	W3	W1	W2	W3	W1	W2	W3	W1	W2	W3	W1	W2	W3	W1	W2	W3
Central																					
Northeast																					
Southeast																					
Southwest																					
Northwest																					
North Central																					
South Central																					

Watch 1 (12 a.m.-8 a.m.) **Watch 2 (8 a.m.-4 p.m.)** **Watch 3 (4 p.m.-12 a.m.)**

Figure A.3: Sample Report Checklist

Reports and Forms Checklist: Watches 1-3
Week 8: April 26-May 2, 2010

Information provided from DPD to PF:

Division	WDA_W1	WDA_W2	WDA_W3	DTR_W1	DTR_W2	DTR_W3	CTF_W1	CTF_W2	CTF_W3
Southwest									
Southeast									
Central									
Northeast									
Northwest									
North Central									
South Central									

Reports provided for DPD from PF:

Division	WDA_W1	WDA_W2	WDA_W3	DTR_W1	DTR_W2	DTR_W3	CTF_W1	CTF_W2	CTF_W3
Southwest									
Southeast									
Central									
Northeast									
Northwest									
North Central									
South Central									

WDA- Web-Based Deployment Application
DTR- Deployment Report
CTR- Compstat Target Form
W- Watch

The processes described in this Appendix were designed to allow us to collect both intended deployment data and AVL data in various time intervals so that we could investigate the relationship between AVL and police deployment and crime.

Appendix C: Additional tables

Table C1A1: Raw patrol intended by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
Total model	Corrected Model	2799862.3314	7	399980.33331	4.693***	Low	847.48(88.01)	610.18(92.31)
	Intercept	94084598.104	1	94084598.104	1104.011***	Medium	958.23(42.58)	709.93(42.58)
	Assign	880545.93926	1	880545.93926	10.333***	High	921.56(41.28)	912.97(41.28)
	Traj	973876.18177	3	324625.39392	3.809*	Very High	1069.68(103.21)	894.02(97.30)
	Assign * Traj	762275.19186	3	254091.73729	2.982*			
	Error	1908944719089446.926	224	85220.745				
	Total	198045329.026	232					
Week 1	Corrected Model	17023.157	7	2431.88880	5.724***	Low	41.31(6.51)	52.09(6.21)
	Intercept	430018.34342	1	430018.34342	1012.156***	Medium	50.37(3.00)	55.99(3.00)
	Assign	955.404	1	955.404	2.249	High	69.01(2.91)	67.64(2.91)
	Traj	15588.791	3	5196.264	12.231***	Very High	62.31(6.87)	69.35(7.28)
	Assign * Traj	1023.316	3	341.105	0.803			
	Error	95167.299	224	424.854				
	Total	949133.77765	232					
Week 2	Corrected Model	11056.245	7	1579.464	6.157***	Low	47.01(5.06)	57.58(4.82)
	Intercept	432815.7698	1	432815.7698	1687.221***	Medium	49.54(2.33)	68.47(2.33)
	Assign	3022.025	1	3022.025	11.781***	High	62.04(2.26)	61.44(2.26)
	Traj	1678.952	3	559.651	2.182	Very High	56.58(5.33)	66.92(5.66)
	Assign * Traj	4642.299	3	1547.433	6.032***			
	Error	57461.784	224	256.526				
	Total	897724.02022	232					
Week 3	Corrected Model	9287.062	7	1326.723	5.772***	Low	45.66(4.79)	58.38(4.57)
	Intercept	416443.96962	1	416443.96962	1811.864***	Medium	48.73(2.21)	64.93(2.21)
	Assign	3974.497	1	3974.497	17.292***	High	59.23(2.14)	60.08(2.14)
	Traj	1398.593	3	466.198	2.028	Very High	54.20(5.05)	69.43(5.36)
	Assign * Traj	3112.825	3	1037.608	4.514**			
	Error	51484.808	224	229.843				
	Total	840512.43430	232					
Week 4	Corrected Model	12669.475	7	1809.925	5.697***	Low	41.95(5.63)	57.73(5.37)
	Intercept	433024.57571	1	433024.57571	1363.084***	Medium	49.54(2.59)	67.97(2.59)
	Assign	4109.104	1	4109.104	12.935***	High	61.34(2.52)	63.18(2.52)
	Traj	3085.169	3	1028.39390	3.237*	Very High	59.15(5.94)	68.85(6.30)
	Assign * Traj	3500.418	3	1166.806	3.673*			
	Error	71160.343	224	317.68680				
	Total	915153.53527	232					
Week 5	Corrected Model	11590.508	7	1655.787	5.486***	Low	46.56(5.49)	61.46(5.23)
	Intercept	463325.65654	1	463325.65654	1535.228***	Medium	50.26(2.53)	66.87(2.53)

	Assign	3815.443	1	3815.443	12.642***	High	64.87(2.45)	65.10(2.45)
	Traj	3449.698	3	1149.899	3.810*	Very High	59.19(5.79)	71.54(6.14)
	Assign * Traj	3512.084	3	1170.695	3.879**			
	Error	67602.305	224	301.796				
	Total	954661.23230	232					
Week 6	Corrected Model	12669.475	7	1809.925	5.697***	Low	41.96(7.13)	51.99(6.80)
	Intercept	433024.57571	1	433024.57571	1363.084***	Medium	49.56(3.28)	67.22(3.28)
	Assign	4109.104	1	4109.104	12.935***	High	63.20(3.18)	60.93(3.18)
	Traj	3085.169	3	1028.39390	3.237*	Very High	64.63(7.51)	75.41(7.97)
	Assign * Traj	3500.418	3	1166.806	3.673*			
	Error	71160.343	224	317.68680				
	Total	915153.53527	232					
Week 7	Corrected Model	11590.508	7	1655.787	5.486***	Low	48.90(9.61)	89.62(9.16)
	Intercept	463325.65654	1	463325.65654	1535.228***	Medium	61.21(4.43)	91.16(4.43)
	Assign	3815.443	1	3815.443	12.642***	High	73.29(4.29)	77.36(4.29)
	Traj	3449.698	3	1149.899	3.810*	Very High	75.15(10.1)	83.21(10.7)
	Assign * Traj	3512.084	3	1170.695	3.879**			
	Error	67602.305	224	301.796				
	Total	954661.23230	232					
Week 8	Corrected Model	25209.666	7	3601.381	3.238**	Low	51.10(10.5)	82.30(10.0)
	Intercept	697005.15152	1	697005.15152	626.712***	Medium	59.31(4.86)	85.50(4.86)
	Assign	8482.983	1	8482.983	7.627**	High	79.44(4.71)	76.65(4.71)
	Traj	3572.887	3	1190.962	1.071	Very High	75.24(11.1)	86.38(11.7)
	Assign * Traj	12071.957	3	4023.986	3.618*			
	Error	249124.08080	224	1112.161				
	Total	1578793.8802	232					
Week 9	Corrected Model	21312.622	7	3044.66660	3.636***	Low	52.31(9.15)	62.95(8.72)
	Intercept	668276.97969	1	668276.97969	797.968***	Medium	60.27(4.22)	71.47(4.22)
	Assign	1469.065	1	1469.065	1.754	High	78.70(4.09)	79.62(4.09)
	Traj	17868.146	3	5956.049	7.112***	Very High	86.80(9.64)	91.40(10.2)
	Assign * Traj	1397.204	3	465.735	0.556			
	Error	187593.95951	224	837.473				
	Total	1430773.5470	232					
Week 10	Corrected Model	25188.667	7	3598.381	3.451**	Low	51.06(10.2)	76.19(9.73)
	Intercept	667732.44435	1	667732.44435	640.337***	Medium	58.17(4.71)	81.73(4.71)
	Assign	12069.88880	1	12069.88880	11.575***	High	76.45(4.56)	79.59(4.56)
	Traj	5994.864	3	1998.288	1.916	Very High	66.75(10.7)	93.35(11.4)
	Assign * Traj	6346.371	3	2115.457	2.029			
	Error	233583.53534	224	1042.784				
	Total	1515395.1052	232					
Week 11	Corrected Model	33228.949	7	4746.993	2.906**	Low	46.76(12.7)	72.03(12.1)
	Intercept	685013.33328	1	685013.33328	419.285***	Medium	57.07(5.89)	86.11(5.89)
	Assign	11129.005	1	11129.005	6.812**	High	76.36(5.71)	77.05(5.71)
	Traj	8920.164	3	2973.388	1.82820	Very High	77.54(13.4)	97.85(14.2)

	Assign * Traj	10384.405	3	3461.468	2.119			
	Error	365963.13126	224	1633.764				
	Total	16657791665778.990	232					
Week 12	Corrected Model	26880.104	7	3840.015	3.030**	Low	47.42(11.2)	61.35(10.7)
	Intercept	628338.08082	1	628338.08082	495.858***	Medium	56.47(5.19)	76.65(5.19)
	Assign	8280.117	1	8280.117	6.534*	High	72.49(5.03)	77.22(5.03)
	Traj	13461.178	3	4487.059	3.541*	Very High	74.05(11.8)	100.15(12.58)
	Assign * Traj	3640.989	3	1213.663	0.958			
	Error	283847.04035	224	1267.174				
	Total	1464442.8801	232					
Week 13	Corrected Model	21268.023	7	3038.289	2.355*	Low	48.15(11.35)	63.73(10.83)
	Intercept	650344.5502	1	650344.5502	504.047***	Medium	59.35(5.23)	74.10(5.23)
	Assign	3612.347	1	3612.347	2.8800	High	76.51(5.07)	75.65(5.07)
	Traj	14545.359	3	4848.453	3.758*	Very High	82.36(11.97)	95.79(12.69)
	Assign * Traj	3458.891	3	1152.964	0.894			
	Error	289015.22218	224	1290.247				
	Total	1493892.6630	232					

Table C2A2: Logged patrol intended by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
Total model	Corrected Model	1.517	7	0.217	7.443***	Low	2.72(0.05)	2.90(0.05)
	Intercept	1056.736	1	1056.736	36281.411***	Medium	2.77(0.02)	2.96(0.02)
	Assign	0.42.420	1	0.42.420	14.406***	High	2.94(0.02)	2.94(0.02)
	Traj	0.495	3	0.165	5.666***	Very High	2.92(0.05)	3.00(0.06)
	Assign * Traj	0.454	3	0.151	5.194**			
	Error	6.524	224	0.029				
	Total	1968.081	232					
Week 1	Corrected Model	2.462	7	0.352	7.203***	Low	1.52(0.06)	1.68(0.06)
	Intercept	369.833	1	369.833	7574.519***	Medium	1.57(0.03)	1.72(0.03)
	Assign	0.254	1	0.254	5.198*	High	1.82(0.03)	1.81(0.03)
	Traj	1.776	3	0.592	12.125***	Very High	1.76(0.07)	1.81(0.07)
	Assign * Traj	0.364	3	0.121	2.484			
	Error	10.937	224	0.049				
	Total	708.441	232					
Week 2	Corrected Model	1.261	7	0.18.180	7.665***	Low	1.61(0.04)	1.75(0.04)
	Intercept	380.718	1	380.718	16202.349***	Medium	1.63(0.02)	1.82(0.02)
	Assign	0.353	1	0.353	15.022***	High	1.78(0.02)	1.78(0.02)
	Traj	0.27.270	3	0.09.090	3.825*	Very High	1.71(0.05)	1.82(0.05)
	Assign * Traj	0.48.480	3	0.16.160	6.812***			
	Error	5.263	224	0.023				
	Total	717.717	232					
Week 3	Corrected Model	0.936	7	0.134	7.295***	Low	1.60(0.04)	1.75(0.04)
	Intercept	379.098	1	379.098	20686.196***	Medium	1.64(0.01)	1.80(0.01)
	Assign	0.354	1	0.354	19.320***	High	1.76(0.01)	1.76(0.01)
	Traj	0.198	3	0.066	3.601*	Very High	1.72(0.04)	1.83(0.04)
	Assign * Traj	0.312	3	0.104	5.683***			
	Error	4.105	224	0.018				
	Total	708.966	232					
Week 4	Corrected Model	1.425	7	0.204	7.795***	Low	1.56(0.05)	1.74(0.04)
	Intercept	379.225	1	379.225	14520.864***	Medium	1.62(0.02)	1.82(0.02)
	Assign	0.425	1	0.425	16.292***	High	1.77(0.02)	1.78(0.02)
	Traj	0.373	3	0.124	4.759**	Very High	1.74(0.05)	1.82(0.05)
	Assign * Traj	0.441	3	0.147	5.625***			
	Error	5.85850	224	0.026				
	Total	716.092	232					
Week 5	Corrected Model	1.651	7	0.236	7.800***	Low	1.58(0.05)	1.77(0.05)
	Intercept	384.54540	1	384.54540	12717.813***	Medium	1.61(0.02)	1.81(0.02)
	Assign	0.476	1	0.476	15.746***	High	1.80(0.02)	1.80(0.02)
	Traj	0.5.500	3	0.167	5.511***	Very High	1.74(0.05)	1.84(0.06)
	Assign * Traj	0.524	3	0.175	5.776***			
	Error	6.773	224	0.03.030				
	Total	724.904	232					
Week 6	Corrected Model	1.176	7	0.168	5.677***	Low	1.57(0.05)	1.69(0.05)
	Intercept	378.332	1	378.332	12788.457***	Medium	1.63(0.02)	1.80(0.02)
	Assign	0.243	1	0.243	8.220**	High	1.77(0.02)	1.75(0.02)
	Traj	0.425	3	0.142	4.793**	Very High	1.77(0.05)	1.85(0.06)
	Assign * Traj	0.408	3	0.136	4.594**			

	Error	6.627	224	0.03.030				
	Total	710.729	232					
Week 7	Corrected Model	1.75750	7	0.25.250	6.792***	Low	1.63(0.06)	1.90(0.05)
	Intercept	419.356	1	419.356	11394.658***	Medium	1.70(0.02)	1.92(0.02)
	Assign	0.607	1	0.607	16.494***	High	1.84(0.02)	1.87(0.02)
	Traj	0.186	3	0.062	1.681	Very High	1.84(0.06)	1.87(0.06)
	Assign * Traj	0.633	3	0.211	5.737***			
	Error	8.244	224	0.037				
	Total	790.703	232					
Week 8	Corrected Model	1.637	7	0.234	5.989***	Low	1.65(0.06)	1.88(0.05)
	Intercept	417.471	1	417.471	10692.329***	Medium	1.69(0.02)	1.89(0.02)
	Assign	0.496	1	0.496	12.699***	High	1.87(0.02)	1.85(0.02)
	Traj	0.326	3	0.109	2.784*	Very High	1.82(0.06)	1.90(0.06)
	Assign * Traj	0.722	3	0.241	6.162***			
	Error	8.746	224	0.039				
	Total	785.893	232					
Week 9	Corrected Model	1.408	7	0.201	5.502***	Low	1.65(0.06)	1.77(0.05)
	Intercept	414.919	1	414.919	11348.560***	Medium	1.70(0.02)	1.83(0.02)
	Assign	0.144	1	0.144	3.940*	High	1.87(0.02)	1.87(0.02)
	Traj	0.939	3	0.313	8.560***	Very High	1.90(0.06)	1.92(0.06)
	Assign * Traj	0.24.240	3	0.08.080	2.186			
	Error	8.19190	224	0.037				
	Total	776.965	232					
Week 10	Corrected Model	1.936	7	0.277	6.056***	Low	1.63(0.06)	1.84(0.06)
	Intercept	409.957	1	409.957	8977.505***	Medium	1.66(0.03)	1.88(0.03)
	Assign	0.704	1	0.704	15.424***	High	1.85(0.03)	1.87(0.03)
	Traj	0.466	3	0.155	3.401*	Very High	1.77(0.07)	1.92(0.07)
	Assign * Traj	0.537	3	0.179	3.917**			
	Error	10.229	224	0.046				
	Total	777.097	232					
Week 11	Corrected Model	2.164	7	0.309	5.192***	Low	1.57(0.07)	1.78(0.07)
	Intercept	403.475	1	403.475	6777.341***	Medium	1.65(0.03)	1.88(0.03)
	Assign	0.592	1	0.592	9.952**	High	1.82(0.03)	1.84(0.03)
	Traj	0.63.630	3	0.21.210	3.528*	Very High	1.84(0.08)	1.92(0.08)
	Assign * Traj	0.613	3	0.204	3.432*			
	Error	13.335	224	0.06.060				
	Total	765.568	232					
Week 12	Corrected Model	1.8800	7	0.257	4.075***	Low	1.59(0.07)	1.72(0.07)
	Intercept	397.288	1	397.288	6295.019***	Medium	1.65(0.03)	1.84(0.03)
	Assign	0.488	1	0.488	7.725**	High	1.79(0.03)	1.83(0.03)
	Traj	0.732	3	0.244	3.864**	Very High	1.82(0.08)	1.96(0.08)
	Assign * Traj	0.318	3	0.106	1.677			
	Error	14.137	224	0.063				
	Total	750.506	232					
Week 13	Corrected Model	1.734	7	0.248	3.899***	Low	1.57(0.07)	1.74(0.07)
	Intercept	401.115	1	401.115	6313.497***	Medium	1.66(0.03)	1.83(0.03)
	Assign	0.399	1	0.399	6.281*	High	1.81(0.03)	1.83(0.03)
	Traj	0.905	3	0.302	4.746**	Very High	1.86(0.08)	1.96(0.08)
	Assign * Traj	0.311	3	0.104	1.63630			
	Error	14.231	224	0.064				
	Total	755.202	232					

Table C3: Raw AVL patrol by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
Total model	Corrected Model	18723827.004	4	4680956.8751	4.675***	Low	1050.87(228.95)	1078.87(227.14)
	Intercept	22001312222 0013121.546	1	220013122 220013121.545	219.731***	Medium	918.90(122.35)	946.90(122.35)
	Assign	45443.979	1	45443.979	0.045	High	1267.59(119.71)	1295.59(119.71)
	Traj	1870094018 700939.819	3	6233646.6606	6.226***	Very High	1994.31(250.44)	2022.30(252.46)
	Error	22729153822 7291537.648	227	1001284.3307				
	Total	5657475475 65747546.537	232					
Week 1	Corrected Model	113884.2202	4	28471.051	4.972***	Low	75.91(17.31)	80.15(17.17)
	Intercept	1289863.8793	1	1289863.8793	225.239***	Medium	70.28(9.25)	74.52(9.25)
	Assign	1045.515	1	1045.515	0.183	High	96.43(9.05)	100.68(9.05)
	Traj	113142.61611	3	37714.204	6.586***	Very High	153.74(18.94)	157.9(19.09)
	Error	1299945.9856	227	5726.634				
	Total	3305772.5472	232					
Week 2	Corrected Model	134234.41409	4	33558.602	5.197***	Low	78.82(18.38)	83.10(18.24)
	Intercept	1392745.7705	1	1392745.7705	215.675***	Medium	71.18(9.82)	75.46(9.82)
	Assign	1061.876	1	1061.876	0.164	High	101.20(9.61)	105.48(9.61)
	Traj	133494.38377	3	44498.126	6.891***	Very High	160.92(20.11)	165.20(20.27)
	Error	1465875.5498	227	6457.601				
	Total	3629715.5535	232					
Week 3	Corrected Model	111674.89892	4	27918.723	4.356**	Low	84.36(18.31)	85.63(18.17)
	Intercept	1403089.8797	1	1403089.8797	218.941	Medium	75.51(9.78)	76.77(9.78)
	Assign	93.174	1	93.174	0.015	High	99.47(9.57)	100.74(9.57)
	Traj	111653.13134	3	37217.711	5.808***	Very High	160.37(20.03)	161.64(20.19)
	Error	1454735.8769	227	6408.528				
	Total	35943583 594357.998	232					
Week 4	Corrected Model	102715.61605	4	25678.901	4.005**	Low	84.83(18.32)	87.06(18.17)
	Intercept	1364047.6623	1	1364047.6623	212.740***	Medium	73.79(9.79)	76.02(9.79)
	Assign	287.379	1	287.379	0.045	High	99.65(9.57)	101.88(9.57)
	Traj	102560.82815	3	34186.938	5.332***	Very High	153.60(20.04)	155.82(20.20)
	Error	1455479.1053	227	6411.802				
	Total	3560655.3303	232					
Week 5	Corrected Model	117860.63627	4	29465.157	4.273**	Low	82.39(19.00)	84.33(18.85)
	Intercept	1391930.1119	1	1391930.1119	201.840***	Medium	73.92(10.15)	75.86(10.15)
	Assign	217.143	1	217.143	0.031	High	101.06(9.93)	102.99(9.93)
	Traj	117766.75751	3	39255.584	5.692***	Very High	159.32(20.78)	161.25(20.95)
	Error	1565439.049	227	6896.207				

	Total	3716519.9888	232						
Week 6	Corrected Model	107443.19187	4	26860.797	4.063**		Low	81.04(18.60)	83.72(18.45)
	Intercept	1292577.3345	1	1292577.3345	195.522***		Medium	70.32(9.94)	73.00(9.94)
	Assign	417.119	1	417.119	0.063		High	96.62(9.72)	99.30(9.72)
	Traj	107194.37369	3	35731.456	5.405***		Very High	151.93(20.35)	154.61(20.51)
	Error	1500678.3344	227	6610.918					
	Total	3485292.3259	232						
Week 7	Corrected Model	100449.28282	4	25112.321	4.326**		Low	84.10(17.43)	85.60(17.29)
	Intercept	1245833.6569	1	1245833.6569	214.607***		Medium	68.51(9.31)	70.00(9.31)
	Assign	128.937	1	128.937	0.022		High	95.21(9.11)	96.70(9.11)
	Traj	100397.11108	3	33465.703	5.765***		Very High	147.08(19.06)	148.57(19.22)
	Error	1317776.9926	227	5805.185					
	Total	3212173.1057	232						
Week 8	Corrected Model	104870.49486	4	26217.622	4.637***		Low	79.33(17.20)	80.58(17.06)
	Intercept	1219719.8773	1	1219719.8773	215.717***		Medium	68.40(9.19)	69.66(9.19)
	Assign	91.14140	1	91.14140	0.016		High	93.95(8.99)	95.20(8.99)
	Traj	104846.06060	3	34948.687	6.181***		Very High	149.50(18.82)	150.75(18.97)
	Error	1283518.5548	227	5654.267					
	Total	3143473.4446	232						
Week 9	Corrected Model	127609.29286	4	31902.322	5.333***		Low	84.93(17.69)	85.94(17.55)
	Intercept	1347664.8753	1	1347664.8753	225.270***		Medium	69.40(9.45)	70.41(9.45)
	Assign	59.501	1	59.501	0.01.010		High	100.41(9.25)	101.42(9.25)
	Traj	127600.41405	3	42533.468	7.110***		Very High	157.05(19.35)	158.07(19.51)
	Error	1358012.8805	227	5982.435					
	Total	3411344.1086	232						
Week 10	Corrected Model	108947.5496	4	27236.874	4.533**		Low	77.20(17.73)	78.95(17.59)
	Intercept	1257588.4442	1	1257588.4442	209.278***		Medium	70.41(9.47)	72.16(9.47)
	Assign	176.623	1	176.623	0.029		High	96.12(9.27)	97.87(9.27)
	Traj	108877.81808	3	36292.603	6.040***		Very High	152.52(19.40)	154.27(19.55)
	Error	1364081.9857	227	6009.171					
	Total	3310822.7734	232						
Week 11	Corrected Model	120811.39388	4	30202.847	5.421***		Low	79.06(17.07)	81.85(16.94)
	Intercept	131403413 14033.976	1	13140341314033.976	235.870***		Medium	69.86(9.12)	72.64(9.12)
	Assign	449.552	1	449.552	0.081		High	100.09(8.92)	102.88(8.92)
	Traj	120546.2198	3	40182.066	7.213***		Very High	154.04(18.68)	156.83(18.83)
	Error	1264616.9900	227	5571.000					
	Total	3318810.5505	232						
Week 12	Corrected Model	98554.964	4	24638.741	4.207***		Low	82.12(17.51)	83.65(17.37)
	Intercept	1241626.4386	1	1241626.4386	211.988***		Medium	69.46(9.35)	70.98(9.35)
	Assign	135.003	1	135.003	0.023		High	94.40(9.15)	95.93(9.15)

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
	Traj	98501.89890	3	32833.963	5.606***	Very High	148.17(19.15)	149.70(19.30)
	Error	1329553.2174	227	5857.062				
	Total	3220313.2191	232					
Week 13	Corrected Model	98780.229	4	24695.057	4.275**	Low	76.71(17.39)	78.25(17.25)
	Intercept	1175755.2192	1	1175755.2192	203.527***	Medium	67.81(9.29)	69.35(9.29)
	Assign	138.384	1	138.384	0.024	High	92.92(9.09)	94.46(9.09)
	Traj	98728.143	3	32909.381	5.697***	Very High	146.00(19.02)	147.55(19.17)
	Error	1311354.5459	227	5776.892				
	Total	3123756.3266	232					

Table C4: Logged AVL patrol by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
Total model	Corrected Model	2.08080	4	0.52.520	9.331***	Low	2.89(0.05)	2.89(0.05)
	Intercept	1142.637	1	1142.637	20499.522***	Medium	2.89(0.02)	2.90(0.02)
	Assign	0.001	1	0.001	0.014	High	3.03(0.02)	3.04(0.02)
	Traj	2.08080	3	0.693	12.441***	Very High	3.21(0.05)	3.21(0.05)
	Error	12.653	227	0.056				
	Total	2079.329	232					
Week 1	Corrected Model	2.328	4	0.582	9.094***	Low	1.74(0.05)	1.75(0.05)
	Intercept	450.225	1	450.225	7035.199***	Medium	1.77(0.03)	1.78(0.03)
	Assign	0.005	1	0.005	0.074	High	1.91(0.03)	1.92(0.03)
	Traj	2.326	3	0.775	12.115***	Very High	2.11(0.06)	2.11(0.06)
	Error	14.527	227	0.064				
	Total	822.053	232					
Week 2	Corrected Model	2.562	4	0.64.640	10.972***	Low	1.75(0.05)	1.76(0.05)
	Intercept	458.344	1	458.344	7853.153***	Medium	1.78(0.02)	1.79(0.02)
	Assign	0.007	1	0.007	0.118	High	1.93(0.02)	1.95(0.02)
	Traj	2.558	3	0.853	14.610***	Very High	2.12(0.06)	2.13(0.06)
	Error	13.249	227	0.058				
	Total	835.698	232					
Week 3	Corrected Model	1.959	4	0.49.490	7.915***	Low	1.78(0.05)	1.78(0.05)
	Intercept	458.805	1	458.805	7415.145***	Medium	1.79(0.03)	1.80(0.03)
	Assign	0.003	1	0.003	0.049	High	1.92(0.02)	1.93(0.02)
	Traj	1.958	3	0.653	10.547***	Very High	2.11(0.06)	2.12(0.06)
	Error	14.045	227	0.062				
	Total	834.853	232					
Week 4	Corrected Model	1.817	4	0.454	7.338***	Low	1.80(0.05)	1.80(0.05)
	Intercept	457.248	1	457.248	7385.576***	Medium	1.79(0.03)	1.79(0.03)
	Assign	0.002	1	0.002	0.037	High	1.92(0.02)	1.93(0.02)
	Traj	1.816	3	0.605	9.779***	Very High	2.08(0.06)	2.09(0.06)
	Error	14.054	227	0.062				
	Total	832.953	232					
Week 5	Corrected Model	2.036	4	0.509	8.544***	Low	1.77(0.05)	1.77(0.05)
	Intercept	457.731	1	457.731	7681.968***	Medium	1.79(0.02)	1.80(0.02)

	Assign	0.000	1	0.000	0.006	High	1.93(0.02)	1.93(0.02)
	Traj	2.036	3	0.679	11.393***	Very High	2.11(0.06)	2.11(0.06)
	Error	13.526	227	0.06.060				
	Total	835.438	232					
Week 6	Corrected Model	2.019	4	0.505	8.137***	Low	1.77(0.05)	1.78(0.05)
	Intercept	449.095	1	449.095	7238.716***	Medium	1.77(0.03)	1.77(0.03)
	Assign	0.003	1	0.003	0.040	High	1.91(0.02)	1.92(0.02)
	Traj	2.018	3	0.673	10.844***	Very High	2.07(0.06)	2.08(0.06)
	Error	14.083	227	0.062				
	Total	818.44440	232					
Week 7	Corrected Model	1.985	4	0.496	8.475***	Low	1.79(0.05)	1.79(0.05)
	Intercept	449.465	1	449.465	7676.661***	Medium	1.76(0.02)	1.76(0.02)
	Assign	0.000	1	0.000	0.002	High	1.91(0.02)	1.91(0.02)
	Traj	1.985	3	0.662	11.299***	Very High	2.08(0.06)	2.08(0.06)
	Error	13.291	227	0.059				
	Total	813.833	232					
Week 8	Corrected Model	2.07070	4	0.518	8.272***	Low	1.77(0.05)	1.77(0.05)
	Intercept	445.767	1	445.767	7125.452***	Medium	1.76(0.03)	1.75(0.03)
	Assign	0.002	1	0.002	0.030	High	1.90(0.02)	1.89(0.02)
	Traj	2.066	3	0.689	11.008***	Very High	2.09(0.06)	2.08(0.06)
	Error	14.201	227	0.063				
	Total	808.144	232					
Week 9	Corrected Model	2.328	4	0.582	9.799***	Low	1.79(0.05)	1.79(0.05)
	Intercept	456.106	1	456.106	7677.566***	Medium	1.77(0.02)	1.77(0.02)
	Assign	0.001	1	0.001	0.010	High	1.93(0.02)	1.93(0.02)
	Traj	2.326	3	0.775	13.054***	Very High	2.11(0.06)	2.10(0.06)
	Error	13.486	227	0.059				
	Total	826.582	232					
Week 10	Corrected Model	2.092	4	0.523	8.460***	Low	1.76(0.05)	1.75(0.05)
	Intercept	447.542	1	447.542	7240.778	Medium	1.77(0.03)	1.77(0.03)
	Assign	0.006	1	0.006	0.089	High	1.92(0.02)	1.91(0.02)
	Traj	2.082	3	0.694	11.231***	Very High	2.09(0.06)	2.08(0.06)
	Error	14.031	227	0.062				
	Total	816.844	232					
Week 11	Corrected Model	2.461	4	0.615	10.467***	Low	1.75(0.05)	1.76(0.05)
	Intercept	452.607	1	452.607	7698.897***	Medium	1.77(0.02)	1.78(0.02)
	Assign	0.005	1	0.005	0.077	High	1.93(0.02)	1.94(0.02)
	Traj	2.459	3	0.82.820	13.945***	Very High	2.09(0.06)	2.10(0.06)
	Error	13.345	227	0.059				
	Total	828.254	232					
Week 12	Corrected Model	1.817	4	0.454	6.908***	Low	1.77(0.05)	1.77(0.05)
	Intercept	444.751	1	444.751	6764.487***	Medium	1.77(0.03)	1.77(0.03)
	Assign	0.000	1	0.000	0.000	High	1.90(0.03)	1.90(0.03)
	Traj	1.816	3	0.605	9.209***	Very High	2.07(0.06)	2.07(0.06)
	Error	14.925	227	0.066				
	Total	810.73730	232					
Week 13	Corrected Model	2.249	4	0.562	8.685***	Low	1.73(0.05)	1.74(0.05)
	Intercept	439.116	1	439.116	6781.541***	Medium	1.74(0.03)	1.75(0.03)

Assign	0.006	1	0.006	0.097
Traj	2.246	3	0.749	11.563***
Error	14.699	227	0.065	
Total	800.687	232		

High	1.89(0.03)	1.90(0.03)
Very High	2.07(0.06)	2.08(0.06)

Table C5: Raw crime by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C Mean (SD)	T Mean (SD)
Total model	Corrected Model	400110.94940	4	100027.74735	144.892***	Low	72.54(6.01)	70.41(5.96)
	Intercept	2518361.7667	1	2518361.7667	3647.905***	Medium	103.13(3.21)	100.99(3.21)
	Assign	263.753	1	263.753	0.382	High	148.18(3.14)	146.05(3.14)
	Traj	399346.97970	3	133115.66657	192.821***	Very High	246.12(6.57)	243.98(6.62)
	Error	156711.33331	227	690.358				
	Total	4429153.000	232					
Week 1	Corrected Model	2219.836	4	554.959	46.154***	Low	5.55(0.79)	5.31(0.78)
	Intercept	13842.329	1	13842.329	1151.230***	Medium	7.56(0.42)	7.32(0.42)
	Assign	3.456	1	3.456	0.287	High	11.07(0.41)	10.82(0.41)
	Traj	2212.591	3	737.53530	61.338***	Very High	18.23(0.86)	17.98(0.87)
	Error	2729.435	227	12.024				
	Total	26135.000	232					
Week 2	Corrected Model	2494.289	4	623.572	35.950***	Low	4.85(0.95)	5.04(0.94)
	Intercept	14493.568	1	14493.568	835.568***	Medium	7.76(0.50)	7.95(0.50)
	Assign	2.175	1	2.175	0.125	High	10.59(0.49)	10.78(0.49)
	Traj	2494.013	3	831.338	47.927***	Very High	19.32(1.04)	19.51(1.05)
	Error	3937.487	227	17.346				
	Total	28098.000	232					
Week 3	Corrected Model	2142.593	4	535.648	41.369***	Low	5.76(0.82)	5.75(0.81)
	Intercept	14288.993	1	14288.993	1103.573***	Medium	7.62(0.43)	7.61(0.43)
	Assign	0.009	1	0.009	0.001	High	10.94(0.43)	10.93(0.43)
	Traj	2141.749	3	713.916	55.137***	Very High	18.30(0.90)	18.28(0.90)
	Error	2939.182	227	12.948				
	Total	26748.000	232					
Week 4	Corrected Model	2384.679	4	596.17170	37.178***	Low	6.46(0.91)	6.21(0.90)
	Intercept	15479.852	1	15479.852	965.335***	Medium	7.75(0.48)	7.50(0.48)
	Assign	3.505	1	3.505	0.219	High	11.69(0.47)	11.44(0.47)
	Traj	2377.433	3	792.478	49.419***	Very High	18.93(1.00)	18.69(1.01)
	Error	3640.11110	227	16.036				
	Total	29365.000	232					
Week 5	Corrected Model	2745.183	4	686.296	38.272***	Low	5.02(0.96)	4.34(0.96)
	Intercept	15967.16160	1	15967.16160	890.433***	Medium	8.97(0.51)	8.29(0.51)
	Assign	26.846	1	26.846	1.497	High	12.32(0.50)	11.63(0.50)
	Traj	2707.097	3	902.366	50.322***	Very High	20.08(1.05)	19.40(1.06)
	Error	4070.541	227	17.932				
	Total	32562.000	232					
Week 6	Corrected Model	3178.264	4	794.566	47.987***	Low	5.67(0.93)	5.11(0.92)
	Intercept	15700.008	1	15700.008	948.195***	Medium	7.69(0.49)	7.13(0.49)
	Assign	18.005	1	18.005	1.087	High	11.38(0.48)	10.83(0.48)
	Traj	3150.678	3	1050.226	63.428***	Very High	21.02(1.01)	20.46(1.02)
	Error	3758.615	227	16.558				
	Total	29226.000	232					
Week 7	Corrected Model	2252.27270	4	563.067	37.957***	Low	5.83(0.88)	5.60(0.87)
	Intercept	15271.405	1	15271.405	1029.467***	Medium	8.22(0.47)	7.99(0.47)

	Assign	3.01010	1	3.01010	0.203	High	12.05(0.46)	11.82(0.46)
	Traj	2245.714	3	748.571	50.462***	Very High	18.40(0.96)	18.17(0.97)
	Error	3367.381	227	14.834				
	Total	30179.000	232					
Week 8	Corrected Model	2185.386	4	546.346	34.802***	Low	6.27(0.90)	6.47(0.89)
	Intercept	15991.418	1	15991.418	1018.635***	Medium	8.08(0.48)	8.29(0.48)
	Assign	2.442	1	2.442	0.156	High	11.22(0.47)	11.43(0.47)
	Traj	2184.864	3	728.288	46.391***	Very High	19.07(0.99)	19.28(0.99)
	Error	3563.644	227	15.699				
	Total	29817.000	232					
Week 9	Corrected Model	2648.121	4	662.03030	34.478***	Low	5.96(1.00)	5.57(0.99)
	Intercept	15889.204	1	15889.204	827.491***	Medium	8.11(0.53)	7.71(0.53)
	Assign	9.054	1	9.054	0.472	High	11.51(0.52)	11.12(0.52)
	Traj	2632.603	3	877.534	45.701***	Very High	20.12(1.09)	19.73(1.10)
	Error	4358.776	227	19.202				
	Total	30528.000	232					
Week 10	Corrected Model	2389.795	4	597.449	38.642***	Low	5.03(0.89)	4.96(0.89)
	Intercept	15173.349	1	15173.349	981.398***	Medium	8.38(0.48)	8.31(0.48)
	Assign	0.28.280	1	0.28.280	0.018	High	11.65(0.47)	11.58(0.47)
	Traj	2387.709	3	795.903	51.478***	Very High	18.97(0.98)	18.90(0.99)
	Error	3509.636	227	15.461				
	Total	30192.000	232					
Week 11	Corrected Model	2888.033	4	722.008	53.407***	Low	5.23(0.84)	4.97(0.83)
	Intercept	15482.018	1	15482.018	1145.200***	Medium	7.90(0.44)	7.64(0.44)
	Assign	3.982	1	3.982	0.295	High	11.91(0.43)	11.64(0.43)
	Traj	2879.304	3	959.768	70.994***	Very High	19.82(0.92)	19.56(0.92)
	Error	3068.825	227	13.519				
	Total	29781.000	232					
Week 12	Corrected Model	1868.839	4	467.21210	29.095***	Low	5.13(0.91)	5.51(0.90)
	Intercept	13560.568	1	13560.568	844.468***	Medium	7.68(0.48)	8.07(0.48)
	Assign	8.717	1	8.717	0.543	High	10.80(0.47)	11.19(0.47)
	Traj	1864.145	3	621.382	38.696***	Very High	17.11(1.00)	17.49(1.01)
	Error	3645.192	227	16.058				
	Total	27277.000	232					
Week 13	Corrected Model	1742.354	4	435.589	31.547***	Low	5.39(0.85)	5.00(0.84)
	Intercept	11437.956	1	11437.956	828.389***	Medium	6.95(0.45)	6.57(0.45)
	Assign	8.444	1	8.444	0.612	High	10.42(0.44)	10.03(0.44)
	Traj	1729.315	3	576.438	41.748***	Very High	16.12(0.93)	15.73(0.93)
	Error	3134.297	227	13.807				
	Total	22797.000	232					

Table C6A6: Logged crime by treatment and trajectory group

	Source of variability	Type III Sum of Squares	df	Mean Square	F	Trajectory	C	T
Total model	Corrected Model	4.061	4	1.015	123.108***	Low	1.83(0.02)	1.83(0.02)
	Intercept	552.153	1	552.153	66949.521***	Medium	2.00(0.01)	1.99(0.01)
	Assign	0.000	1	0.000	0.051	High	2.16(0.01)	2.16(0.01)
	Traj	4.058	3	1.353	164.016***	Very High	2.38(0.02)	2.37(0.02)
	Error	1.872	227	0.008				
	Total	1011.789	232					
Week 1	Corrected Model	3.511	4	0.878	39.677***	Low	0.77(0.03)	0.76(0.03)
	Intercept	125.384	1	125.384	5666.976***	Medium	0.90(0.01)	0.89(0.01)
	Assign	0.001	1	0.001	0.049	High	1.06(0.01)	1.05(0.01)
	Traj	3.507	3	1.169	52.839***	Very High	1.26(0.03)	1.26(0.03)
	Error	5.022	227	0.022				
	Total	232.748	232					
Week 2	Corrected Model	3.888	4	0.972	28.043***	Low	0.70(0.04)	0.72(0.04)
	Intercept	122.761	1	122.761	3542.177***	Medium	0.90(0.02)	0.92(0.02)
	Assign	0.023	1	0.023	0.667	High	1.02(0.02)	1.04(0.02)
	Traj	3.875	3	1.292	37.266***	Very High	1.28(0.04)	1.30(0.04)
	Error	7.867	227	0.035				
	Total	232.157	232					
Week 3	Corrected Model	3.432	4	0.858	26.836***	Low	0.78(0.04)	0.77(0.04)
	Intercept	126.076	1	126.076	3943.218***	Medium	0.90(0.02)	0.89(0.02)
	Assign	0.004	1	0.004	0.126	High	1.05(0.02)	1.05(0.02)
	Traj	3.423	3	1.141	35.687***	Very High	1.27(0.04)	1.26(0.04)
	Error	7.258	227	0.032				
	Total	234.38380	232					
Week 4	Corrected Model	3.469	4	0.867	30.280***	Low	0.81(0.03)	0.80(0.03)
	Intercept	129.996	1	129.996	4538.365***	Medium	0.91(0.02)	0.90(0.02)
	Assign	0.007	1	0.007	0.252	High	1.07(0.02)	1.06(0.02)
	Traj	3.456	3	1.152	40.217***	Very High	1.28(0.04)	1.27(0.04)
	Error	6.502	227	0.029				
	Total	240.415	232					
Week 5	Corrected Model	4.495	4	1.124	38.474***	Low	0.71(0.03)	0.67(0.03)
	Intercept	127.905	1	127.905	4379.227***	Medium	0.96(0.02)	0.93(0.02)
	Assign	0.087	1	0.087	2.973	High	1.10(0.02)	1.06(0.02)
	Traj	4.383	3	1.461	50.026***	Very High	1.31(0.04)	1.27(0.04)
	Error	6.63630	227	0.029				
	Total	248.955	232					
Week 6	Corrected Model	4.272	4	1.068	33.940***	Low	0.76(0.04)	0.74(0.04)
	Intercept	127.207	1	127.207	4042.382***	Medium	0.90(0.02)	0.88(0.02)
	Assign	0.027	1	0.027	0.86.860	High	1.05(0.02)	1.03(0.02)
	Traj	4.231	3	1.41410	44.821***	Very High	1.33(0.04)	1.31(0.04)
	Error	7.143	227	0.031				
	Total	234.128	232					
Week 7	Corrected Model	3.277	4	0.819	32.324***	Low	0.81(0.03)	0.79(0.03)
	Intercept	131.67670	1	131.67670	5194.861***	Medium	0.93(0.01)	0.92(0.01)

	Assign	0.015	1	0.015	0.595	High	1.09(0.01)	1.07(0.01)
	Traj	3.254	3	1.085	42.788***	Very High	1.28(0.03)	1.26(0.04)
	Error	5.754	227	0.025				
	Total	245.833	232					
Week 8	Corrected Model	2.82820	4	0.705	25.916***	Low	0.82(0.03)	0.84(0.03)
	Intercept	132.985	1	132.985	4888.150***	Medium	0.92(0.02)	0.94(0.02)
	Assign	0.022	1	0.022	0.813	High	1.05(0.01)	1.07(0.01)
	Traj	2.806	3	0.935	34.381***	Very High	1.27(0.04)	1.29(0.04)
	Error	6.176	227	0.027				
	Total	243.854	232					
Week 9	Corrected Model	3.28280	4	0.82.820	25.384***	Low	0.81(0.04)	0.81(0.04)
	Intercept	130.416	1	130.416	4036.636***	Medium	0.90(0.02)	0.90(0.02)
	Assign	0.000	1	0.000	0.002	High	1.06(0.02)	1.06(0.02)
	Traj	3.28280	3	1.093	33.839***	Very High	1.28(0.04)	1.28(0.04)
	Error	7.334	227	0.032				
	Total	239.514	232					
Week 10	Corrected Model	3.723	4	0.931	37.278***	Low	0.72(0.03)	0.74(0.03)
	Intercept	128.101	1	128.101	5130.746***	Medium	0.93(0.01)	0.95(0.01)
	Assign	0.021	1	0.021	0.831	High	1.06(0.01)	1.08(0.01)
	Traj	3.711	3	1.237	49.547***	Very High	1.27(0.03)	1.28(0.03)
	Error	5.668	227	0.025				
	Total	244.511	232					
Week 11	Corrected Model	4.32320	4	1.08080	38.256***	Low	0.75(0.03)	0.74(0.03)
	Intercept	128.945	1	128.945	4567.610***	Medium	0.91(0.02)	0.90(0.02)
	Assign	0.003	1	0.003	0.101	High	1.08(0.02)	1.07(0.02)
	Traj	4.312	3	1.437	50.914***	Very High	1.30(0.04)	1.30(0.04)
	Error	6.408	227	0.028				
	Total	241.859	232					
Week 12	Corrected Model	3.106	4	0.777	25.537***	Low	0.74(0.03)	0.77(0.03)
	Intercept	123.451	1	123.451	4059.529***	Medium	0.90(0.02)	0.92(0.02)
	Assign	0.035	1	0.035	1.162	High	1.03(0.02)	1.06(0.02)
	Traj	3.082	3	1.027	33.781***	Very High	1.22(0.04)	1.25(0.04)
	Error	6.903	227	0.03.030				
	Total	233.939	232					
Week 13	Corrected Model	3.422	4	0.855	26.305***	Low	0.74(0.04)	0.74(0.04)
	Intercept	115.202	1	115.202	3542.338***	Medium	0.84(0.02)	0.84(0.02)
	Assign	0.000	1	0.000	0.000	High	1.02(0.02)	1.02(0.02)
	Traj	3.421	3	1.14140	35.064***	Very High	1.20(0.04)	1.20(0.04)
	Error	7.382	227	0.033				
	Total	216.197	232					

About the Authors

Dr. Karen L. Amendola is the Chief Operating Officer of the Police Foundation's Division of Research, Evaluation, and Professional Services. She has 20 years of experience in law enforcement testing, training, research, technology, and assessment. Dr. Amendola earned both her Master of Arts and Doctor of Philosophy degrees in Industrial and Organizational Psychology at George Mason University. Karen recently served as Principal Investigator (with Weisburd and colleagues) for a National Institute of Justice funded study on the impact of shift work on performance, health, safety, fatigue, sleep, overtime, and quality of life published in the *Journal of Experimental Criminology* (Dec. 2011) with related reports at http://policefoundation.org/indexShiftExperiment.html. Amendola is a member of the Academy of Criminal Justice Sciences, American Psychological Association, American Society of Criminology and its Division of Experimental Criminology, as well as the Society for Industrial and Organizational Psychology. Karen recently (2008 - 2012) served first as Vice-Chair and then Chairman of the National Partnership for Careers in Law, Public Safety, Corrections, and Security. In addition Amendola served on the Scientific Review Board of the precursor organization to the National Academy of Credibility Assessment from 2001 - 2007, and has served on the Research Advisory Board of the Innocence Project (New York City) since 2008.

Ms. Breanne Cave is currently a research assistant at George Mason University. Ms. Cave has research experience in assessments of the organizational and crime prevention effects of police technology, implementing experiments in policing, and assessing public perceptions surrounding the use surveillance and information technology by the police. She has extensive knowledge of statistical analysis software, GIS systems, and police tactical software. She is enrolled in the Criminology, Law, and Society program at George Mason University, and has an M.A. in Justice Administration from Norwich University.

Dr. Elizabeth Groff, Co-Principal Investigator is an Assistant Professor at Temple University. Dr. Groff has extensive experience in the application of geographic information systems (GIS) to both research and practice. She has been involved in technology projects in several police agencies and is particularly interested in improving the use of technology to improve the effectiveness of police officers and prevent crime. Dr. Groff has a Ph.D. in Geography and an M.A. in Criminology and Criminal Justice from the University of Maryland, College Park.

Mr. Greg Jones, Co-Principal Investigator is the Research and Crime Mapping Coordinator at the Police Foundation. He has research experience in shift work practices, development, and analysis of survey instruments for police agencies and communities, biased policing, mall security, and domestic violence. He has also serves as a trainer for crime mapping, crime analysis, and problem analysis. He has extensive knowledge of various geographical information systems, tactical software, and various extensions including ArcView, Spatial Analyst, and Automated Tactical Analysis of Crime (A.T.A.C). He has an M.A. in Criminology and Criminal Justice from the University of Maryland, College Park.

Professor David Weisburd, Principal Investigator, is Distinguished Professor of Criminology, Law and Society, and Director of the Center for Evidence-Based Crime Policy at George Mason University in Virginia, and Walter E. Meyer Professor of Law and Criminal Justice and Director of the Institute of Criminology of the Hebrew University Faculty of Law in Jerusalem. Professor Weisburd is an elected Fellow of the American Society of Criminology and of the Academy of

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