J Exp Criminol (2011) 7:321–345
DOI 10.1007/s11292-011-9133-9

License plate reader (LPR) police patrols in crime hot spots: an experimental evaluation in two adjacent jurisdictions

Cynthia Lum · Julie Hibdon · Breanne Cave · Christopher S. Koper · Linda Merola

Published online: 16 August 2011

Abstract
Objectives This randomized controlled experiment tests whether license plate readers (LPR) deter crime generally, and automobile crime more specifically in crime hot spots. The limited intervention tested here reflects one current likely use of LPR at the time of this publication.
Methods We use a place-based block randomized experiment. Our subjects were 30 hot spots in two jurisdictions, 15 which were assigned to experimental conditions. The treatment involved targeted police patrols using a "sweep and sit" approach with license plate readers in these hot spots, also applying the Koper Curve timing principle. We examine effects of the intervention during and in a 30-day period post-intervention, controlling for pre-intervention levels of crime, seasonal factors, and jurisdiction.
Results Our findings indicate that, when small numbers of LPR patrols are used in crime hot spots in the way we have tested them here, they do not seem to generate either a general or offense-specific deterrent effect.
Conclusions While we did not find significant findings of this intervention, a number of limitations and caveats to this study must be considered in conjunction with these findings. The authors suggest how already acquired LPRs might be used in ways that might increase their effectiveness in crime hot spots.

Keywords Experiment · Police · License plate reader · Technology · Hot spots · Autotheft

Introduction

License plate reader (LPR) technology, also known as automated number plate recognition (ANPR), is a scanning and information technology used by law

C. Lum (✉) · J. Hibdon · B. Cave · C. S. Koper · L. Merola
Department of Criminology, Law and Society, Center for Evidence-Based Crime Policy, George Mason University, Fairfax, VA, USA
e-mail: clum@gmu.edu

enforcement agencies to detect, deter, and prevent crime. It has become one of the most rapidly diffusing innovations in law enforcement compared to other police technologies, such as mobile fingerprint readers, facial recognition, gunshot detection devices, video equipment, or aerial surveillance equipment (see Koper et al. 2009). Lum et al. (2010) estimated in a random sample of U.S. police agencies that over a third of all large police agencies already use LPR systems, primarily for the purposes of addressing auto theft (Koper et al. 2009, also found a similar proportion agencies had adopted LPR in their survey). Of departments that do not use LPR, 30% reported they planned to acquire this technology within 12 months of taking the survey. Compared to the adoption of, for example, computerized crime mapping technology (see Weisburd and Lum 2005), LPR's adoption has been quite rapid. This rapid adoption and the associated costs of LPR ($20,000–25,000 per unit) necessitate its evaluation.

The appeal of LPR to police agencies likely reflects its ease of use and prima facie efficiency, values law enforcement officers often attribute to good technology (Chan 2003; Ericson and Haggerty 1997). As an operational tool for law enforcement, LPR is a straightforward and easily understood sensory technology. Although the primary function of LPR has been to detect auto theft, as the vast majority of agencies who use it have attested (Lum et al. 2010), LPR can also be used to detect other civil and criminal wrongdoings of individuals associated with scanned vehicles. A small scanner-camera is placed either on a patrol vehicle or mounted at a fixed location, detecting the numbers and letters on license plates of vehicles that come within its view. The scanner is connected to an information technology system that holds a database of plates "of interest". Plates of interest might include those associated with a recently stolen vehicle or whose registered owners have open warrants, unpaid tickets, or are suspected of existing crimes. Once the LPR scans a plate, the system reads the alphanumeric pattern and then compares the license plate against the database. If a match is found, officers are alerted to proceed with further confirmation, investigation and action. The LPR allows an officer to scan and check hundreds of vehicles within minutes.

LPR technology therefore automates a process that, in the past, was done manually and with much discretion. Without LPR technology, officers might see a car that appeared suspicious and radio a computer-aided dispatch (CAD) center with the plate number to determine its stolen status or the warrant status of its owner.[1] The dispatcher would then check the plate (and its owner) against a database containing stolen automobiles or wanted individuals, and provide the officer with relevant information. This process could take a couple of minutes per vehicle, depending on how the workload of the dispatcher. The advent of in-car computer units eliminated the use of a dispatcher for this purpose. However, whether using the dispatcher or a mobile computer unit, checking vehicles in this manner is done tag-by-tag, and is highly discretionary.

The use of license plate readers automates this manual approach. It also drastically reduces the officer's discretion in deciding which tag to run, since all tags within view are scanned. In some cases, LPR is used for more specialized investigations, including tracking down parents who have failed to pay child support, monitoring whether registered sex offenders are driving around schools or

[1] In some agencies, officers still carry paper lists of stolen vehicles against which to check suspicious vehicles prior to calling the dispatch center.

parks, or to assist with criminal investigations (PA Consulting Group 2003, 2004). Because LPR can also collect and store the dates, times, locations and plate numbers of cars in its range, it can also be used as an information system, proactively locating individuals or tracking offenders based on previously collected data.

Precisely because of these various uses, LPR also presents challenges to police organizations (Lum et al. 2010). Although LPRs automate a once cumbersome and slow manual process, the use of LPR does not necessarily make the police more effective in reducing, preventing, or clearing auto theft or other crimes. Indeed, the effectiveness of LPR is limited by four factors: the system's ability to read license plates accurately; the quality and relevance of the data to which the scanned plates are compared; the way in which police departments deploy the technology; and how the officer decides to use the technology. Improvements in scanning, data access, and police deployment strategies could increase LPR's effectiveness in controlling and preventing crime, although such an effect should not be assumed (Lum 2010). At the same time, as with many other police technologies, advances in each of these functions can challenge other equally important facets of policing. There have been legal concerns about how long data can be stored, the extent to which data can be mined and used, the balance of public interest in privacy and security, and the broader concern of the effects of technology on police legitimacy (International Association of Chiefs of Police 2009; Lum et al. 2010).

Although all these concerns are important, this paper focuses on evaluating the crime control effectiveness of LPR. Specifically, we examine its effectiveness at auto theft hot spots, partially replicating the experiment conducted by Taylor et al. (2011), but adding new caveats. In that experiment, the research team examined the effectiveness of LPR on auto thefts in a single jurisdiction, comparing manual approaches to using LPR along predicted routes of stolen autos. We also employ a randomized controlled trial, but extend our study to two adjacent jurisdictions in the Washington, D.C. area. Further, we not only examine LPR's effect at auto theft hot spots, but also the effect of LPR patrols on other crimes. Both the Taylor et al. and this study diverge from previous analyses of LPR technology, in that we examine the *prevention and deterrence* of auto theft and other crimes in hot spots rather than only LPR's efficiencies in detecting and recovering stolen autos.

All in all, we did not find an effect of the use of LPR in experimental hot spots, a similar finding of Taylor et al. However, we explore possible reasons for our findings, given the limited intervention we tested, and make suggestions to law enforcement agencies on how to maximize the use of already-acquired technology.

The current state of research evidence on the effects of LPR technology

License plate readers are one of the more expensive tools of law enforcement, costing approximately \$20,000–25,000 per unit. Given its cost, understanding how LPR achieves the desired functions of the police—to detect, deter, control, reduce and prevent crime—should be a policy priority. Yet, the crime prevention effects and cost-effectiveness of LPR, like many police technologies, remain under-evaluated. Prior to the Taylor et al. (2011) study, LPR research focused primarily on the functioning and efficiency of the technology in scanning license plates or detecting stolen automobiles (and making arrests) in various settings. The Home Office of the United Kingdom has been at the forefront of this research, as well as the funding and use of LPR technology for policing more generally. From 2003 to 2007, the Home Office and PA Consulting Group published a series of assessments and deployment guidelines for license plate readers (see PA Consulting Group 2003, 2004; Home Office 2007). These studies tracked the efficiency of LPR in increasing the detection/recovery of stolen vehicles, as well as increasing drug and weapon seizures. Results from pilot and follow-up studies indicated that license plate readers significantly enhanced the ability of officers to make arrests, particularly when officers were dedicated to a specially designated LPR unit.

Similarly, studies of LPR use in North America have focused on LPR efficiency rather than effectiveness in crime prevention. A study conducted by the Ohio State Highway Patrol (2005), for example, examined the use of LPR in the detection of stolen vehicles and stolen vehicle plates in highway and turnpike systems. In that 4-month evaluation, the use of LPR increased stolen vehicle recoveries and arrests compared to the previous year. In another study, Cohen et al. (2007) analyzed data concerning the rates of scanned plates that matched a database of uninsured, prohibited, unlicensed, or stolen vehicle drivers in British Columbia. The research team found that, regardless of the location of the LPR unit, more detections were associated with more scans per patrol. In a Maryland-based analysis, LPR was found to be efficient in scanning license plates and determining traffic density in various settings, such as highways, parking lots, or tollbooths (Maryland State Highway Authority 2005).

While the study of the functioning and efficiency of LPR technology is necessary in building knowledge about its potential, it is also important to examine how well the technology prevents and deters crime. In police evaluation research, this distinction between implementation efficiencies and outcome effectiveness is crucial, not only because the second does not naturally follow from the first but also because of the costs associated with the use of these technologies. Especially with law enforcement technologies, efficiency is often mistakenly interpreted for effectiveness, which can perpetuate a false belief that crime prevention is occurring (Lum 2010). While LPR may certainly increase auto theft detections and even arrests, such activities may not lead to measurable reductions in crime or even traffic accidents. Indeed, increased arrests and detections may indicate an increase in crime within a jurisdiction or neighborhood. On the other hand, there may be no crime prevention or deterrence effects because the increase in arrests from the use of LPR is low. Further, auto theft trends over time may not provide an accurate assessment of the effects of LPR use. Auto theft has been on the decline for many years, according to the Federal Bureau of Investigation's Uniform Crime Reports, and is likely due to changes in automobile anti-theft technology.

Thus, despite the undisputed advantages of LPR being more efficient than manual approaches, we still must question whether this technology is more *effective* in reducing, preventing, or even detecting crime. Experimental evaluation can assist with this goal. Prior to this study, there has been only one other experimental evaluation of license plate readers that examined their crime prevention potential, conducted by Taylor et al. (2011) around the time this study was commissioned. Taylor et al. measured the effect of the use of license plate readers by specialized auto theft units on rates of vehicle theft along likely routes between stolen and recovery locations of vehicles as well as hot "zones" of stolen and recovery locations. Their findings suggest that, while LPR technology significantly enhances rates of license plates checked, recoveries of stolen cars, and apprehension of auto thieves, the number of plates scanned does not itself predict a reduction of vehicle theft rates.

Hot spots policing and auto crimes: The intervention tested

Like the Taylor et al. (2011) study, our research moves away from examining the efficiencies of LPR technology, and focuses on its crime control effectiveness in crime hot spots using a directed patrol approach. Why evaluate the use of LPR at crime hot spots using directed patrols? Although police technologies can be evaluated in many ways, research is arguably the most practical when the strongest methods of evaluation (experimentation) test the practical, yet optimal deployment of that technology. "Practical" and "optimal" deployment jointly means that the evaluations, while constrained by the limitations of use of an intervention, uses strategies and tactics shown to be most effective through sound experimental research (Lum 2009; Sherman 1998; Weisburd and Eck 2004).

In the case of the practicality of LPR interventions, we know from the national survey conducted by Lum et al. (2010) that police agencies usually only have one to two LPR units, and that they are primarily used by uniformed patrol offices to detect stolen vehicles. Thus, evaluating the effectiveness of LPR by having large number of LPR units saturate areas across the city does not reflect the reality of the current state of this technology.

What would be the "optimal" way to deploy LPR within these practical constraints? Although there is little research on the optimal deployment of LPR for crime prevention, there is a wealth of existing evidence that provides general guidance (see the *Evidence-based Policing Matrix* by Lum et al. 2009s; see also National Research Council 2004; Sherman et al. 1997, 2002; Weisburd and Eck 2004). One of the most successful interventions evaluated for crime prevention and deterrence has involved directing patrol vehicles to targeted "hot spots" of crime. Indeed, the National Research Council deemed the research on hot spots policing to be the "strongest collective evidence of police effectiveness that is now available" (NRC 2004: 250). This conclusion is based on positive findings of numerous experimental evaluations of targeted police patrol at concentrations of crime (see e.g., Braga et al. 1999; Braga and Bond 2008; Sherman and Weisburd 1995; Weisburd and Green 1995). The totality of the research has also indicated that tailored, focused, and proactive approaches at hot spots seem to have a greater effect on crime reduction and prevention than more general approaches (Lum et al. 2011; Weisburd and Eck 2004). Thus, a hot spots approach to LPR patrol seems viable and valid.

Further, a hot spots approach relies on the geographic concentration of crime, of which there is ample research knowledge (selected examples include Brantingham and Brantingham 1981; Pierce et al. 1988; Rengert 1997; Sherman et al. 1989; Sherman and Weisburd 1995; Weisburd et al. 2009, 2004). Evidence of this concentration does not only exist for crime as a general phenomenon but also to specific types of crimes—auto theft included (see, generally, Maxfield and Clarke 2004; see also Barclay et al. 1995; Copes 1999; Sherman et al. 1989). Sherman et al.'s research found that all auto thefts in Minneapolis occurred in less than 3% of the entire city's addresses. Thus, it is generally reasonable to apply a hot spots approach to auto theft prevention and deterrence just as one might apply hot spots policing to drug, violence, or other property crimes, which also cluster in geographic space.

On the other hand, auto thefts have a unique quality in that the location of the crime in question may implicate multiple locations (Lu 2003). For instance, a vehicle might be stolen from one location and then driven from that place to another (the crime is still “in progress”), only to be left at yet another location. Considering this uniqueness, can a hot spots approach be applied to auto theft? Research by Lu (2003) and Lu and Thill (2003) provide insight into the spatial clustering of theft and recovery locations. In these studies, it was found that the journey between theft and recovery locations is shorter than expected, and that the locations where vehicles are recovered are spatially concentrated and in close proximity to theft locations are clustered. Lu recommends that, “[o]ther things being equal, the locations close to offense places should always be checked first for recovery [of stolen automobiles] purposes” (Lu 2003: 430–431).

From a practical perspective, insights from the project team of the Taylor et al. study also prove helpful. In the first phase of their project, Taylor and colleagues deployed officers at predicted “hot routes” between auto theft and recovery locations. However, they found that officers became easily bored with going up and down the same small street segments. Additionally, it appeared that auto theft and recovery locations were in roughly similar areas, and in the second phase of their study, the authors used a zonal approach that encompassed larger areas (approximately 1.2 miles wide). Unlike Taylor et al. (2011), we did not deploy officers at predicted “hot routes” between auto theft and recovery locations as recovery locations were unavailable. While we had limited knowledge of vehicle recovery locations in this study, given the previous research, it is not unreasonable to assign officers to hot spots of auto crimes to create a prevention and deterrent effect given the previous research findings on the close spatial relationship between auto theft and recovery.

Building from this evidence base, the intervention tested here deploys LPR in small and clearly delineated crime hot spots of auto theft, theft from auto (including stolen license plates), and auto-related crimes (e.g., drunk and reckless driving). Testing for both a generalized deterrence and also an offense-specific deterrent effect of LPR is an additional contribution to the Taylor et al. experiment.

The research team was also informed by existing evidence that points to the effectiveness of tailored, proactive, and well-supervised approaches in crime hot spots. For our intervention, we tested the following approach. Officers would “sweep” the entire hot spot at least once so that all vehicles parked or moving in that spot were scanned by the LPR. Then, depending on the particular hot spot, officers would use their discretion to do what they thought worked best for that location. In our study, this usually meant officers strategically positioning their vehicles in certain locations within the assigned hot spot in which they felt the probability of a stolen vehicle passing by would be greatest (such as a busy intersection or a frequently used car park). We often called this combined approach a “sweep and sit” scheme, which contrasts with a “fixed location” use of LPR or a completely mobile use of LPR. This approach was similarly used by Taylor et al. (2011).

Finally, existing research also provides some clues on the optimal timing of police patrol in hot spots. The Koper Curve Principle (see Koper 1995) found there are diminishing marginal deterrent effects for each minute that an officer lingers in a very small hot spot. In other words, to maximize the effectiveness of a hot-spot policing approach, the Koper Curve Principle suggests that officers should not stay in hot spots for long periods of time but rather move from hot spot to hot spot, staying for short time periods (ideally no longer than 12–15 minutes). This approach can also be more cost-effective; in some cities there may be too many hot spots and not enough patrol resources to provide round-the-clock coverage of all hot spots. For our experiment (and unlike Taylor et al. 2011), we decided upon a time limit of 30 minutes for officers to stay within any one particular hot spot, and then had them move to another randomly selected hot spot after 30 minutes. Each day, we gave officers a list of randomly chosen hot spots in which to visit according to the order in which they appeared on that list. Given that each jurisdiction only had two LPR units available for deployment (see below), we felt this modified application of the Koper Curve was practically useful.

Experimental design and implementation

Identifying hot spots for LPR Patrols

The hot spots chosen for this study come from two adjacent jurisdictions—Alexandria City and Fairfax County, Virginia. Fairfax County is one of the larger northern Virginia suburban counties outside of Washington, D.C., with a population of approximately 1 million persons (2010 U.S. Census) and 1,370 sworn officers. Alexandria City is a denser city immediately adjacent to Washington, D.C.'s southwest border, with a population of approximately 150,000 and 320 sworn officers. Alexandria City shares its western border, defined by a major interstate highway, with Fairfax County. Both Alexandria Police Department (APD) and Fairfax County Police Department (FCPD) have progressive and willing senior command and civilian staffs who support this and other evaluation research in their agencies, which was key to the successful completion of this experiment.

We designed a two-step process to derive the hot spots for this study, reflecting both principles and theories of crime at places as well as practical crime prevention concerns. The first step included creating computer-generated hot spots, while the second involved adjusting the hot spots manually with officers to be environmentally meaningful. First, we sought to create small hot spots of crime in which to carry out the experimental intervention. A number of place-based criminologists—notably, Sherman et al. (1989), Sherman and Weisburd (1995), Weisburd (2002, 2008), and Weisburd et al. (2009)—have argued that the size of hot spots matters for both theory and practice. Specifically, there can be discernible variations of crime—as well as areas without crime—within neighborhoods believed to be "dangerous." Thus, patrolling larger geographic areas may actually be less efficacious in accurately targeting crime hot spots. Further, Weisburd et al. (2004) found that crime trends at very small and specific places are stable and often drive an entire city's crime rates. These findings are supplemented by strong empirical evidence, which finds that, when police direct their patrol to small, "micro" places of crime, they can have a significant crime prevention effect (Lum et al. 2011; Weisburd and Eck 2004). Thus, creating small, "micro" hot spots was a priority for this study.

To identify concentrations of crime to create our hot spots, we used ArcGIS[2] to geocode data on auto thefts, thefts from autos and auto related crimes for both jurisdictions.[3] We then ran kernel density analysis to identify hot spots (see Bailey and Gatrell 1995). To confirm the kernel density results, we also created STAC hot spots through CrimeStat.[4] Overall, we ran nine different STAC simulations for each study site (settings of three, five, and 10 incidents per ¼, ½, and 1 mile) in order to get the best picture of hot-spot distributions.

We further narrowed our study area to include all of Alexandria City and only the eastern portion of Fairfax County for several reasons. First, the auto theft and theft from auto incidents had high densities and clustering at the border areas of the two jurisdictions. Additionally, most of the auto-related incidents in Fairfax County fall within the eastern half of the county, close to its border with Alexandria City. Last, by narrowing the focus of our study area, we were able to fine-tune our STAC and kernel density settings and analysis to better identify smaller, more micro-level, auto-incident-related hot spots for our experiment.

After deciding on the new study area, we merged the two jurisdictions into a single geographic database that represented our new dual-jurisdiction area. We then reran the kernel-density simulations using a search radius of 252 feet, and the STAC simulations (at ¼, ½, and 1 mile distances). Overall, reducing the total search area for hot spots resulted in much better representations of hot spots, shown in Fig. 1.

However, even though we had the ability to accurately map micro-crime clusters, we did not only rely on these initial maps for officer deployment in this experiment. First, the boundaries of computer-generated hot spots are often vague. Although the initial hot spots may make statistical sense, they often do not make operational or environmental sense. For example, an environmental barrier (e.g., river, park, railway, business area) can divide a hot spot, making it difficult to cross by offenders or officers. Second, hot spots have to be small enough to accommodate not only our intervention, but hot spots policing evidence more generally, and the Koper Curve Principle, which for our intervention, requires officers to be able to sweep the entire hot spot in under 30 minutes. Third, if police delineate large areas that encompass both hot and cold areas, this could lead to not only an unnecessary spreading out of scarce resources but also to a watering down of the effects in these areas. On the other hand, hot spots which are too small can lead to officer loss of motivation and boredom. Therefore, it is necessary to inform hot spot policing by not only place-based theories and spatial analysis but also environmental considerations and operational context.

To strike this balance, we met with officers and supervisors from each agency who were familiar with these areas. Based on these meetings and other considerations, we readjusted our 40 initial hot spots to 45 new hot spots, sometimes

[2] ArcGIS is a product of the ESRI Corporation (see www.esri.com).

[3] The final geocoding match rate of crime data addresses to x–y coordinates was 91.6% for FCPD and 99.5% for APD. The lower match rate for FCPD could reflect a number of factors, although we suspect it is due to FCPD's relative newness to crime analysis, mapping, and a new records management system. It may also be due to the varied and expanded geographic terrain of Fairfax County compared with Alexandria City.

[4] CrimeStat is a free spatial analysis program available through the National Institute of Justice and the Inter-university Consortium for Political and Social Research (ICPSR). See http://www.icpsr.umich.edu/icpsrweb/CRIMESTAT/ for details on the program.

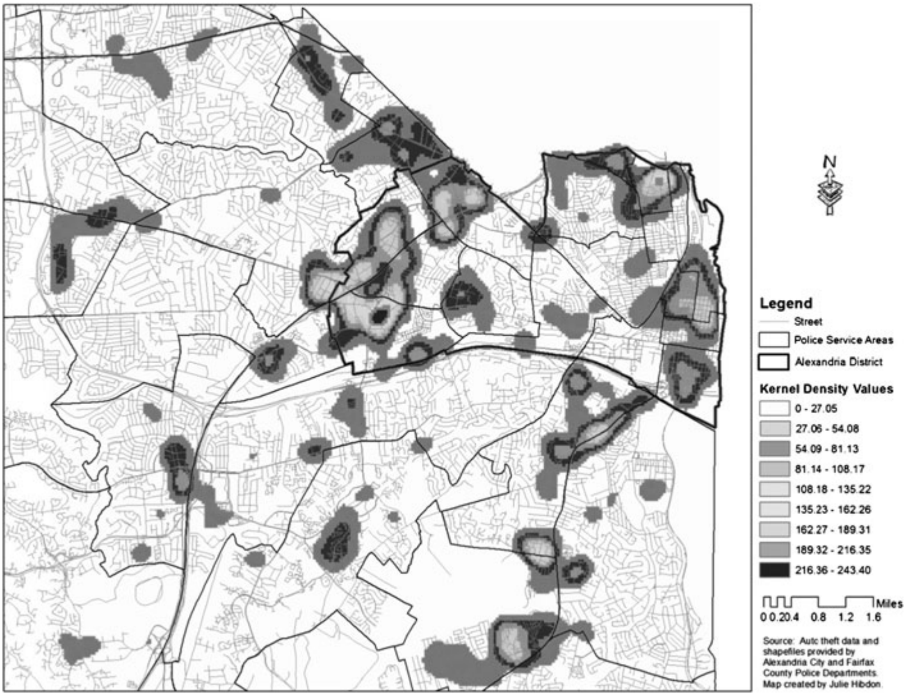


Fig. 1 Mapped hot spots of crime

breaking up hot spots and more carefully redrawing borders to reflect environmental realities. After further consultation with each agency concerning the patrol resources they would be able to provide to our experiment, we further reduced our study area and did not include the eastern portion of Alexandria. This reduced our field of study to 30 hot spots (shown in Fig. 2), which was manageable with the resources we had available to us for this experiment. The average number of auto thefts in these hot spots varied from 5 to 41 incidents during our data collection period (January 2008 through September 2009), with an average in each hot spot during the data collection period of 20.23 incidents and a standard deviation of 9.412. The average area of the hot spots selected for this study varied in size from 0.06 square miles to 0.5 square miles, with an average of 0.24 square miles and standard deviation of 0.105 square miles. As Fig. 2 shows, some hot spots were on or near the border between Alexandria City and Fairfax County, while others were not, creating an excellent and unique opportunity for a multi-jurisdiction study.

Conducting the experiment

In this study, we use a place-based randomized control design, which is highly regarded as providing believable results when evaluating patrol crime prevention strategies (Boruch et al. 2000; Weisburd 2000). Of the 30 hot spots, we randomly assigned 15 to receive the LPR deployment intervention, while the other 15 received "business as usual" policing (no change in the existing police activities in that area). The hot spot assignment to experimental and control groups was kept from the

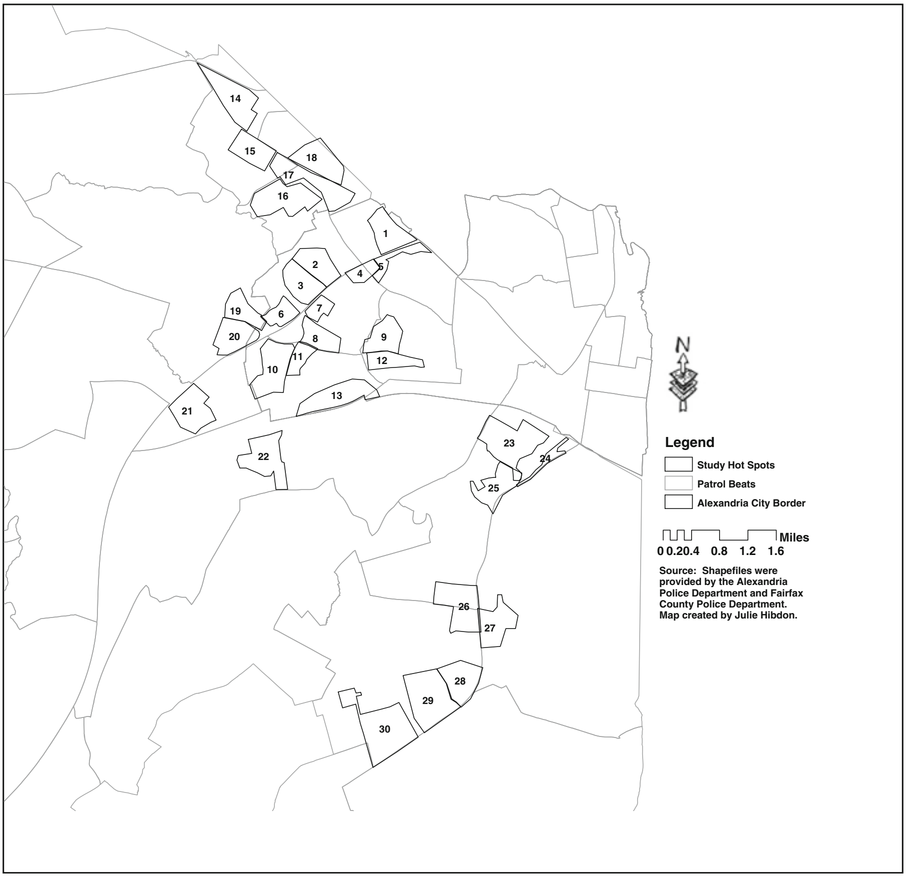


Fig. 2 Thirty final demarcated hot spots used for experiment

officers involved. To select approximately equal number of hot spots from each jurisdiction (13 of the hot spots fell in APD's jurisdiction and 17 in FCPD's jurisdiction), we block-randomized by jurisdiction, randomly selecting 7 from Alexandria City and 8 from Fairfax County to receive the LPR treatment.

Agencies from each jurisdiction allocated two officers and their associated supervisors to this experiment. In order to insure proper implementation, we trained each officer with his or her supervisor on the entire experiment and gave each of them specific instructions about what to do for their daily assignments. By design, the experiment lasted 30 officer working days for each officer. Within each working day, we randomly selected five of the experimental hot spots for each officer to work with LPR each day. Given that each hot spot would require 30 minutes of deployment, and then time getting to and from that hot spot to the next, we anticipated with officer input that five would be a reasonable number of hot spots assigned daily to each officer. Each of the five randomly selected experimental hot spots were printed onto a hot spot assignment sheet and placed into a sealed envelope with an instruction sheet. Each agency received 60 envelopes (30 per officer), which were kept and monitored by a supervisor. Officers received one packet per day for the 30 consecutive working days they were available for the experiment.[5] Once officers completed their daily shift, they would seal all of the materials back into the envelope, and return the packet to their supervisor.

We implemented the experiment on February 22, 2010, for each police department.[6] The Fairfax County Police Department (FCPD) ended its experiment on April 20, 2010, while the Alexandria Police Department (APD) ended its experiment on June 1, 2010. During the time of the experiment, the assigned officers were not required to answer calls for service (unless in emergency or back-up situations). In FCPD, the experiment was implemented by a marked auto theft specialized unit, consisting of one detective from that unit and one patrol officer on detail assigned to this project. Each officer had his own LPR vehicle and was assigned to work during the day. Hence, there is a possibility that both officers worked on the same day and times. Limited resources and shift constraints did not allow the researchers to determine exactly when officers would patrol, although they generally did so during the daylight hours.

The APD implemented the experiment using two patrol officers in marked patrol units from the same district. Because of resource scarcity, the department could assign only one officer per shift to the LPR unit.[7] Additionally, APD officers work 11.5-hour shifts, meaning they only work 3–4 days per week. Consequently, the APD experiment took longer to complete. For the vast majority of the experiment, the officers were able to maintain the experiment and keep to its instructions, including following the specific directions the research team provided if they were unable to complete their daily assignments due to an arrest or other diversion. In only one case, due to an unavoidable personal situation, an officer did not complete his 30-day assignment. It is worth noting that this officer could have completed this assignment, but due to the time restrictions of this project, the GMU team decided to stop the experiment on that officer's 26th experimental day.

Experimental fidelity

Overall, fidelity of the experiment was established by strong initial training, supervision, and detailed instructions included in each daily assignment packet. To ensure correct implementation of the experiment, each agency assigned supervisors to oversee the officers. The research team also visited each agency after approximately 7 working days of the start of the experiment and then subsequently every 10 days or so to pick up folders and make sure the experiment was going as planned.

The daily logs for each patrol sheet indicate there was proper implementation of the experiment and that officers followed the 30-minute per hot spot rule. In the Fairfax County Police Department, of the 300 patrols assigned (five hot spots per

[5] There were days during the experimental period in which officers were not available, which extended both experiments in each jurisdiction further than anticipated.

[6] The start date of the experiment was delayed due to the historic 2010 Washington D.C. area snowstorm. Although most of the snow and ice had been cleared from the roads before the evaluation started, road salt and debris did affect the effectiveness of the plate readers, and snow banks blocked officer access to some parts of hot spots during the first few days of the evaluation. Another factor in the delay was the transition to a new records management system in one of agencies.

[7] The two assigned officers from APD worked opposite patrol shifts (day/evening); thus, although they may have conducted patrols on the same day, there was no overlap of coverage.

day for 30 days for two officers), officers were unable to complete only 20 assignments. Of those 280 assignments completed, almost all (272) stayed within a hot spot for 20–40 minutes. In APD, officers did not complete 44 hot spot patrols primarily because the experiment ended early for one of the two officers. Of these 256 completed assignments, officers spent 20–40 minutes in 248 of them and followed the 30-minute time-in-hot-spot rule strictly in 236 hot spot assignments. Responding to crimes, traffic stops, and family emergencies accounted for many of the missed assignments.

The average number of plate scans within hot spots per 30-minute visit in Fairfax County was 450. The mean number of plates scanned during a hot spot visit ranged from a low of 324 to a high of 601. In Alexandria, the average number of plates scanned within hot spots was 689, ranging from 87 to 1,068.[8] The variation between the number of plate scans can be explained in part by the characteristics of different hotspots—the presence of a busy street near or in the hot spot, the number of cars that are routinely parked in the area, and what happened during the hot spot deployment. The difference in the mean number of plate scans in hot spots was not statistically significant.

Outcomes measured

In our experiment, we measure both the offense-specific and generalized deterrent effects of LPR deployment (see Durlauf and Nagin 2011; Nagin 1998; Sherman 1990). We defined the offense-specific deterrent effect of LPR as the effect the intervention had on the most common target of LPR use—auto related offenses. These include auto theft, theft from auto, and other auto-related crimes (such as driving under the influence and reckless driving). We used all three types of auto-related crimes for several reasons. First, the visibility of marked patrol cars with mounted LPR units could deter these crimes more generally. Second, thefts from autos included stolen license plates, which are detected through the LPR system. Third, breaking into an automobile, whatever the motivation (to steal the car or property within the car), is the first step towards stealing a vehicle and provides the opportunity for the auto theft. Finally, LPR units are often used to detect vehicles whose owners have previous offending histories and suspended licenses for drunk or reckless driving. Including these crimes in our study seemed practical. Table 1 shows the general distributions of our selected measures.

These specific auto-related crimes and also more general crimes were collected from five time periods and include: (1) *pre-intervention period*—counts of crimes prior to the start of the experiment, equivalent to the intervention period for each agency; (2) *intervention period*—the time period during the intervention (APD=99 days; FCPD=58 days); (3) *post intervention period*—30 days after the intervention stopped for each jurisdiction; (4) *seasonal lag of intervention period*—crime counts in the same time period of the intervention from the previous year; and (5) *seasonal post-intervention period*—crime counts for the same 30-day period of the post-intervention period, but for the previous year.

[8] One of the two LPR officers in Alexandria may not have turned off the LPR device in-between hot spots and reported plate read numbers that were unusually high on some days. Although we had the start and end number for reads for the day, we could not be sure that the LPR was not used outside the hot spots (i.e., plates read in between hot spots). Thus, the average for the number of plates scanned in Alexandria was calculated using only one officer's reported numbers.

Table 1 Auto-related crime distributions for the two jurisdictions

Crime type	FCPD	% of total crimes	APD	% of total crimes
All auto-related	2,250	21.5%	655	20.4%
Auto theft and theft from auto	1,018	9.7%	437	13.6%

Percentages shown are of total crimes per jurisdiction

To examine the generalized deterrent effect, we looked at the trends of many different categories of crime and disorder in hot spots potentially affected by the intervention. The reason for measuring a general deterrent effect is that even if auto thefts were not deterred, having a marked patrol unit in these locations may deter other crimes, as evidenced in previous hot spot patrol studies. In our study, we measured generalized deterrence using counts of reports of crimes and disorders, including crimes against persons and property (which included auto-related crimes), weapon-related crimes, disorders, and drug activity. Table 2 provides the counts, for the entire Fairfax County and Alexandria City during the period we implemented the experiment for each jurisdiction, respectively.

Statistical approach and models

Using a randomized controlled experiment, we applied the LPR patrols to our 15 experimental hot spots. We then recorded crimes from each of our three crime categories—all crimes, auto-related crimes, and auto thefts/theft from auto—for each of the five time points at the 30 hot spots. Of interest were differences between treatment and control hot spots for two dependent variables: crimes during the intervention period and in the post-30-day period immediately following the intervention. While the control hot spots reflect the most appropriate counterfactual to the experimental spots, we also incorporated three further controls: the pre-intervention levels of crime; a seasonable covariate that measures crime levels in the same period; and a jurisdiction indicator (whether the intervention and hot spot were located in Alexandria City or Fairfax County).

We also examined the possibility that the effect of the intervention varied across jurisdictions using an interaction term in addition to examining the main effect of the intervention. However, given the imbalanced nature of our design (there are 13 hot

Table 2 General crime distributions for the two jurisdictions

Crime type	FCPD	% of total crimes	APD	% of total crimes
Person	1,225	11.7%	508	15.9%
Property	4,503	43.0%	1,761	55.0%
Disorder	3,959	37.8%	742	23.2%
Drugs and vice	667	6.4%	173	5.4%
Weapons	99	1.0%	19	0.6%
Total crimes	10,453	100.0%	3,203	100.0%

spots in Alexandria and 17 in Fairfax), we focus on the main effects and provide the results of the inclusion of the interaction term cautiously.

Choosing the most appropriate statistical model to examine the effects of the intervention depends on the distribution of the dependent variables. While the distribution of all crimes during the intervention period appears normal, the distributions of auto-related crimes and auto theft/theft from auto were not. In particular, auto crimes are skewed, with most hot spots having zero to one crime. This suggested that linear regression is not an appropriate statistical approach for each of these models, but that perhaps a generalized linear model (Poisson or negative binomial) would be more useful, especially to model specific deterrence. Because there was evidence of over-dispersion in these low crime counts for auto-related crimes, the negative binomial generalized linear model was preferred over the Poisson distribution model for auto-related and auto theft/theft from auto categories (Gardner et al. 1995). However, we did conduct Poisson analyses and found similar findings.

We ran two models. First, we modeled the counts of these different categories of crime in the intervention period compared to the pre-intervention period, controlling for seasonal variation. Second, we modeled the counts of these different categories of crime in the post-intervention period compared to the pre-intervention period, also controlling for seasonal variation. The models specified were:

All crimes (general linear models)

Model 1: modeling the intervention period

$$Y(Tx) = \beta_0 + \beta_1(x^{tx}) + \beta_2(x^{pre}) + \beta_3(x^{seasonTx}) + \beta_4(x^{ju}) + [\beta_5(x^{juINT})]$$

Model 2: modeling the post-intervention period

$$Y(POST) = \beta_0 + \beta_1(x^{tx}) + \beta_2(x^{pre}) + \beta_3(x^{seasonPOST}) + \beta_4(x^{ju}) + [\beta_5(x^{juINT})]$$

Where

β_0	= Intercept
x^{Tx}	= Intervention (experiment=1, control=0)
x^{pre}	= Crime levels during pre-intervention period
$x^{seasonTx}$ or $x^{seasonPOST}$	= Seasonal covariate; indicates crime levels in the same period of dependent variable, but one year prior. The addition of "*Tx*" or "*POST*" matches the dependent variable being measured.
x^{ju}	= A dummy variable for the jurisdiction (APD=1, FCPD=0)
$[x^{juINT}]$	=Interaction term between the location of the hot spot (APD or FCPD) and the intervention given. This term was not included in the main models that were run.

In addition, for auto-related and auto theft/theft from auto crimes, the variable names remain the same as above. Here, we also included in the model the natural log of an "offset" or exposure variable, ln(*offset*). The offset variable indicates the number of days (99 or 58) that a hot spot was exposed to the intervention:

Auto-related and auto theft/theft from auto crimes only (negative binomial models)

Model 1: modeling the intervention period

$$\mu(Tx) = \exp\left[\beta_0 + \beta_1(x^{tx}) + \beta_2(x^{pre}) + \beta_3\left(x^{seasonTx}\right) + \beta_4\left(x^{ju}\right) + \left[\beta_5\left(x^{juINT}\right)\right] + \ln(offset)\right]$$

Model 2: modeling the post-intervention period

$$\mu(POST) = \exp[\beta_0 + \beta_1(x^{tx}) + \beta_2(x^{pre}) + \beta_3(x^{seasonPOST}) + \beta_4(x^{ju}) + [\beta_5(x^{juINT})]] + \ln(offset)$$

Results

Table 3 shows the counts for the hot spots per jurisdiction for each crime categorization and for each period measured. Table 4 then displays the mean values across the 30 hot spots of the experiment in the pre-, during, and post-intervention periods.

Table 3 Mean counts of crimes for hot spots by jurisdiction and measure for Fairfax County (*FCPD*) and Alexandria City (*APD*)

	FCPD (17 hot spots)		APD (13 hot spots)	
	Mean	SD	Mean	SD
All crimes				
Pre-intervention	52.24	24.004	71.31	45.644
During intervention	86.41	41.384	77.77	46.494
Post-intervention	41.12	20.068	17.85	12.233
Seasonal intervention (2009)	82.65	43.190	66.00	37.076
Seasonal post-intervention (2009)	44.53	24.567	25.38	15.570
Auto-related[a]				
Pre-intervention	12.82	6.635	17.00	13.916
During intervention	16.71	9.835	16.54	12.190
Post-intervention	6.88	3.295	3.77	3.059
Seasonal intervention (2009)	9.06	5.309	13.15	7.679
Seasonal post-intervention (2009)	7.94	4.981	6.69	5.407
Auto theft/theft from auto				
Pre-intervention	7.12	3.407	14.62	13.035
During intervention	6.24	3.882	12.23	8.691
Post-intervention	2.76	2.223	2.69	2.689
Seasonal intervention (2009)	4.94	2.817	9.77	6.698
Seasonal post-intervention (2009)	2.71	1.312	4.62	2.755

[a] *Auto-related* means auto theft, theft from auto, and other auto-related offenses such as driving under the influence and reckless driving

Table 4 Mean counts of crime in the control and experimental group combined by period measured

	Control or experiment	Mean	SD	SE	Min	Max
All crimes						
Pre-intervention	Control	60.87	39.379	10.168	15	149
	Experiment	60.13	32.935	8.504	12	151
	Total	60.50	35.671	6.513	12	151
During intervention	Control	79.67	48.153	12.433	19	164
	Experiment	85.67	38.878	10.038	28	170
	Total	82.67	43.109	7.871	19	170
Post-intervention	Control	32.40	23.591	6.091	3	91
	Experiment	29.67	17.690	4.568	5	60
	Total	31.03	20.535	3.749	3	91
Auto-related crimes						
Pre-intervention	Control	13.80	8.402	2.169	3	28
	Experiment	15.47	12.386	3.198	4	54
	Total	14.63	10.434	1.905	3	54
During intervention	Control	15.33	9.788	2.527	3	32
	Experiment	17.93	11.768	3.039	4	49
	Total	16.63	10.717	1.957	3	49
Post-intervention	Control	5.47	3.758	.970	0	12
	Experiment	5.60	3.376	.872	0	12
	Total	5.53	3.511	.641	0	12
Auto theft/theft from auto						
Pre-intervention	Control	9.60	6.833	1.764	3	23
	Experiment	11.13	11.855	3.061	2	50
	Total	10.37	9.539	1.742	2	50
During intervention	Control	8.07	5.298	1.368	3	20
	Experiment	9.60	8.458	2.184	2	35
	Total	8.83	6.978	1.274	2	35
Post-intervention	Control	2.47	2.642	.682	0	8
	Experiment	3.00	2.171	.561	0	8
	Total	2.73	2.392	.437	0	8

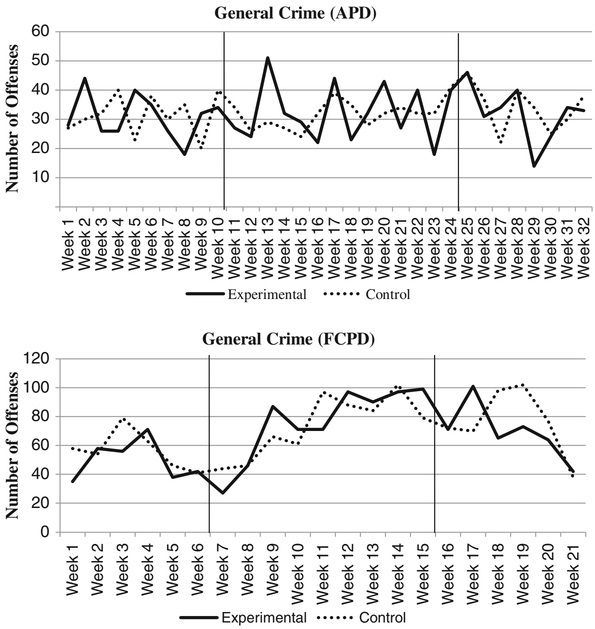
General deterrence of all crimes

Figure 3 shows the weekly counts of all crimes for APD and FCPD during the pre-intervention, intervention, and post-intervention periods. The experimental period is delineated by the vertical lines for each jurisdiction, respectively.[9] No clear pattern emerges from these visualizations between control and experimental groups.

In applying the models when examining the general deterrent effect of LPR patrol, there appeared to be no discernible difference in the levels of crime during or after the intervention period between experimental and control hot spots (Table 5). While on average the experimental hot spots during intervention had approximately

[9] Weekly trends of all crimes for Alexandria from the week of November 15, 2009 ("Week 1") through the week of June 30, 2010 ("Week 32") and for Fairfax County from the week of December 26, 2009 ("Week 1") through the week of May 20, 2010 ("Week 21").

Fig. 3 Weekly trends of all crimes for Alexandria City (*APD*) and Fairfax County (*FCPD*)



4 more crimes, and slightly less crimes (.07 on average) in the post-intervention period, these differences were not statistically significant. In our discussion, we offer suggestions as to why this may have occurred.

It appears that crime levels during the treatment period were best predicted by crime levels in the same period before treatment and during the same period a year prior (the "seasonal effect"). Although crime levels in the post-intervention period were not significantly influenced by crime levels prior to treatment, a seasonal effect was also found. Hot spots in Alexandria City had significantly fewer crimes compared to Fairfax County in the post treatment period, although this was found in both treatment and control groups. Further, the inclusion of the interaction term does

Table 5 Linear regression results for general deterrent effect of LPR

	Model 1 Y(crime levels during treatment Tx)	Model 2 Y(crime POST-intervention)
Constant	10.12 (7.491)	10.13 (4.534)*
Intervention effect (Tx=1)	4.16 (5.932)	-.07 (3.308)
Pre-intervention crime levels	.68 (.151)***	.06 (.071)
Seasonal effect (either Tx or POST in 2009)	.47 (.130)**	.62 (.118)***
Jurisdiction effect	−14.10 (7.626)	−12.60 (4.749)*
Adjusted R^2	.87 (15.801)	.81 (9.031)

Unstandardized β coefficients reported, with standard errors in parentheses

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

not change these substantive results, indicating the effects of the intervention did not differ across the two jurisdictions. Again, we report the inclusion of the interaction term cautiously, given that the unbalanced nature of our sample across the two jurisdictions.

Offense-specific deterrence of auto theft and auto-related crimes

Figure 4a, b shows the weekly counts of auto-related crimes and auto theft/theft from auto for APD and FCPD during the pre-intervention, intervention, and post-intervention periods for each jurisdiction, respectively. Like all crime, no clear pattern emerges from these visualizations between control and experimental groups.

Similarly, we did not discover a statistically significant offense-specific deterrence effect of LPR deployment in hot spots on auto theft or auto-related crimes (Table 6). While there was, on average, 16 and 11% more auto-related crimes in experimental hot spots during and post-intervention, respectively, these differences were not significant. Similarly, experimental hot spots of auto theft exhibited only a miniscule and non-significant difference compared with control hot spots during treatment, and 20% more crime than the treatment group during the post-intervention period (also not significant).[10] While hot spots in Alexandria City had significantly fewer crimes compared to Fairfax County in both the treatment and post treatment periods, this was found in both treatment and control groups. As with all crimes above, the effects of the intervention did not differ across the two jurisdictions.[11]

A note on sensitivity tests for displacement and diffusion

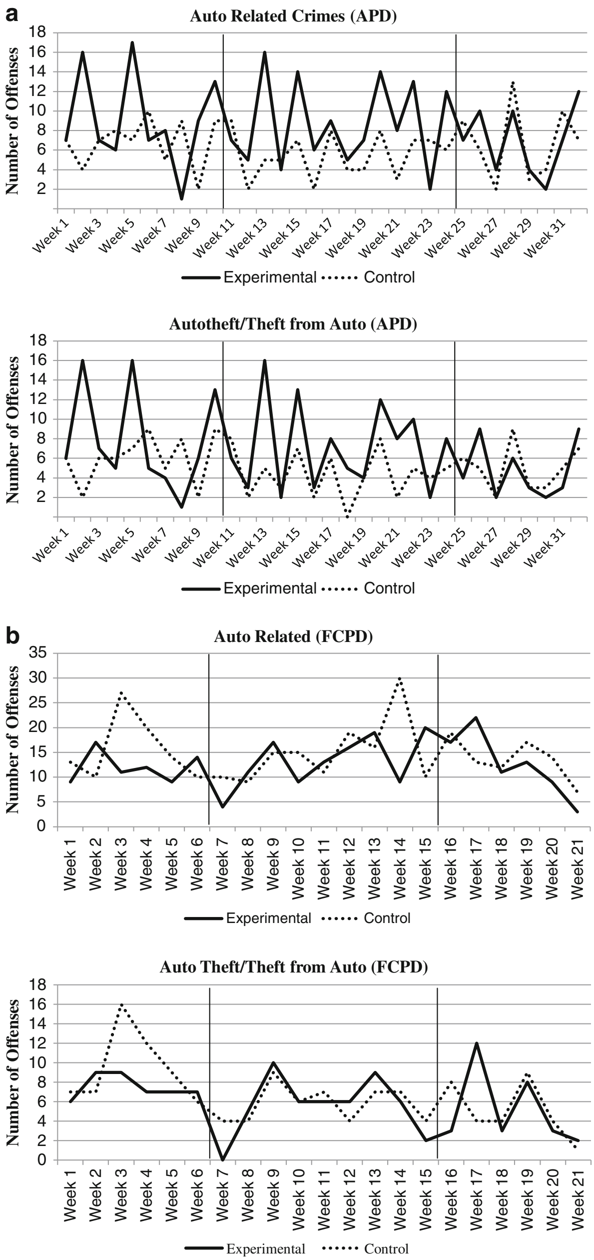
This study was not designed to specifically measure displacement of crime and diffusion of benefits (see Clarke and Weisburd 1994; Weisburd et al. 2006), primarily because of the small number of hot spots and adjacency between some hot spots. Although the individual re-mapping of hot-spot boundaries helped to define areas that were more environmentally distinct, there may be the possibility of displacement of crime and diffusion of benefits to adjacent control hot spots from experimental ones. The limitation on the number of hot spots in these two jurisdictions did not allow for the creation of clearly distinct and separated hot spot locations with non-overlapping buffer zones to measure displacement.

However, to consider the possibility of displacement and diffusion, we ran sensitivity tests for each of our models, controlling for possible effects of the

[10] The large percent differences are due to the low base rates of crime in each experimental and control hot spots.

[11] Again, when including the interaction effect between the intervention and the location of the hot spot, no substantive changes were discovered, with the exception of the significance of the independent jurisdiction effect, which became less significant and greater than.05. It appears that hot spots in Alexandria either during the treatment period or after, had less auto-related thefts recorded in the hot spots, independent of whether the hot spot received or had more or less auto-related crimes during the pre-intervention period or during the year prior.

Fig. 4 **a** Weekly trends of auto-related crimes and auto thefts/thefts for Alexandria City (*APD*). **b**Weekly trends of auto-related crimes and auto thefts/thefts for Fairfax County (*FCPD*)



intervention from experimental to control hot spots. To do this, we created a dummy variable to control for the presence of an adjacent experimental hot spot to a control area. This allowed us to detect whether any differences created by the intervention in an experimental hot spot was the result of displacement or diffusion. The inclusion of this factor in each of the models described above did not significantly influence any of the effects shown.

Table 6 Negative binomial results for specific deterrent effect of LPR

	Auto-related model 1 Y(Tx)	Auto-related model 2 Y(POST)	Auto-THEFT model 1 Y(Tx)	Auto-THEFT model 2 Y(POST)
Intercept (all ***)	−2.22 (.473)	−2.89 (.519)	−2.75 (.406)	−3.63 (.519)
Intervention effect (Tx=1)	.15 (.383)	.10 (.416)	.00 (.393)	.19 (.435)
Pre-intervention crime levels	.04 (.023)	.03 (.030)	.04 (.022)	.04 (.031)
Seasonal effect	.04 (.039)	.03 (.052)	.05 (.045)	.08 (.120)
Jurisdiction effect	−.924 (.400)*	−1.03 (.443)**	-.55 (.487)	−1.14 (.558)*
Chi-square (*df*=25)	4.446	7.914	6.166	14.456
Log-likelihood	−111.326	−80.853	−93.100	−63.486

Unstandardized β coefficients reported, with standard errors in parentheses

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

Discussion of limitations of this study

Past evaluation research on police deployment practices clearly indicates that targeted, hot spot patrol using focused interventions can be very effective in deterring crime at and around those hot spots. However, our findings indicate that, when small numbers of LPR patrols are used in crime hot spots in the way we have tested them here, they do not seem to generate either a general or offense-specific deterrent effect. Taylor et al. (2011) found similar outcomes, even when using more officers across a longer time period in a single jurisdiction. Taylor et al. also found that LPR used in conjunction with traditional hot spots patrol did not result in the same significant reductions in crime compared to hot spots in which an auto theft specialized unit did manual checks (although the traditional hot spot patrols with LPR had detected more stolen automobiles).

Despite these findings, there are interesting lessons that emerge from the limitations of this study. For example, it is possible that the lack of significant difference between treatment and control hot spots in this experiment reflects the weakness in the intensity of the intervention in our experiment. Perhaps if more LPR units were available to deploy to multiple hot spots more often, an effect may be discovered. As with many types of deployment options available to the police, there may be a threshold of dosage that could lead to a deterrent effect. However, because of very limited resources in both APD and FCPD, there was likely only a single vehicle involved in an experiment hot spot at any given time. This intensity differs drastically from other hot spot experiments in which saturation of patrol and an "all-hands-on-deck" approach is employed (Sherman and Weisburd 1995; Weisburd and Green 1995). But the small number of LPR units per jurisdiction is an empirical reality, as Lum and colleagues (2010) found in their national survey. If this limited resource availability of LPR is likely to reflect the normal situation in many agencies that use LPR, we suggest that a combination of LPR units and other auto-theft tactical approaches in hot spots may be more useful in a situation of limited resources. We also hypothesize (although further testing is needed) that a time-sensitive approach in hot spots is more economical. LPR can also be used for many other non auto related offenses, discussed shortly.

Related to this issue is that the sample size in this experiment was small. Thus, the statistical power to detect even a small effect was low. This is an unfortunate problem in many hot spots studies, where the number of hot spots available for analysis (or intervention) are few. Further, unlike Sherman and Weisburd's (1995) experiment, the size of our hot spots, although small, were larger than single addresses or blocks, given the nature of the intervention and crime problem. Increasing the size of hot spots will reduce the available number of hot spots for analysis. Given this limitation, however, it is important to note that we did not find consistent results of the intervention in any particular direction, during or after treatment.

A lack of treatment effect may also be due to the length of time the intervention was implemented, which again, was determined by both the resources available to the researchers and to the police agencies for this field experiment. Ninety-nine and 58 days, respectively, in Alexandria City and Fairfax County may be too short a time to generate a change in the perceptions of individuals from which a deterrent effect might be generated. Perceptions of policies can be important in generating deterrent effects (Nagin 1998), and this may be the case with LPR. However, Taylor et al. (2011) conducted their first experimental phase over 30 weeks and their second phase over 18 additional weeks, also not finding significant effects of LPR on crime reduction. Ultimately, proactive hot spots approaches, since they have been shown to be effective, need to be institutionalized into the regular activities of patrol, rather than housed only within specialized units or a special program or research study. Crime prevention and deterrence interventions in hot spots, because of their stability (Weisburd et al. 2004), require consistent efforts, such as maintaining elevated patrol presence and other problem-solving approaches that keep crime at a minimum. Problem-solving and tailored approaches also imply that the *timing* of the intervention may be important to maximizing crime reduction. In our experiment, we designed the study to work with officer schedules and other responsibilities (i.e., court apperances, training, etc.). The choice of when officers went to hot spots was therefore not tightly controlled. Yet, research indicates that there are temporal variations in crime over time (for a general discussion of this, see Felson and Poulsen 2003; Melbin 1978). Future research should examine the effects of officers in hot spots at "hot times".

Yet another limitation of this research that reflects the realities of policing is the availability of information. LPR is an information technology system and therefore relies on the availability of data from which the system can compare scanned tags. If data are outdated, limited in depth or scope, or not connected to other sources of information, this will hamper the capacity of LPR to detect stolen vehicles or vehicles associated with offenders. At the same time, the data connected to the LPR units in our study reflect what is common in LPR use nationally. Most LPR units connect to a limited set of data concerning stolen automobiles, license plates, and, sometimes, wanted individuals who own those vehicles. These are limits reflected in this experiment. However, expanding the source and connectivity of LPR data can have consequences on citizen privacy and police agency legitimacy, as discussed below.

Finally, it may be the case that the sole use of LPR by uniformed vehicle patrols reduces the deterrent effect of that patrol unit. For example, if an officer is sitting in a fixed location scanning cars passing by, he or she may provide less general coverage of a hot spot, even within 30 minutes, than a roaming car might provide. Alternatively, it might be the case that an officer focusing on LPR "hits" may miss seeing disorders and crimes because they are distracted by the LPR technology. On the other hand, LPR can free the officer from constantly running tags on his or her mobile unit and allow the officer to focus on other tasks. One option that officers might consider is to view LPR as a background-scanning device while focusing on activities that evidence indicates are effective policing strategies (problem solving and proactive patrol in very small hot spots).

Concluding remarks

Given our findings and these limitations, there are a few final considerations that we wish to leave with the reader. First, LPR is rapidly diffusing into American law enforcement, especially among larger agencies. This rapid technological diffusion is occurring irrespective of the evidence about the crime prevention effectiveness of LPR. Indeed, the International Association of Chiefs of Police recommended the acquisition of LPR technology for police agencies prior to an experimental evaluation of its crime control or prevention effectiveness.[12] In 2008, the Department of Homeland Security Urban Area Security Initiative (UASI)[13] did just that, and, in northern Virginia and the District of Columbia alone, $4.4 million was allocated for jurisdictions to acquire LPR (Virginia Department of Emergency Management, 2008). While this study and Taylor et al. (2011) have found that LPR does not achieve a prevention or deterrent effect in the way it was tested here, the many limitations of this study emphasize that there may be other ways LPR might be used to generate a crime control effect that have not yet been tested. These uses may have nothing to do with auto thefts; indeed, auto thefts have been declining for some years, mostly due to auto theft technology in cars and keys. In terms of cost-effectiveness, finding ways to get the most out of LPR units already purchased may be the impetus for more evaluation on what could be an optimal use of LPR for crime prevention or deterrence.

Our experiments reveal that we have to think more carefully about ways to optimize the effectiveness of technologies given the many mandates for which the police are responsible (i.e., reducing crime, maintaining legitimacy in democratic society, achieving cost-savings, etc.). It could be the case that the effects of LPR are masked by logistical issues related to the technology. For instance, greater frequency of hot spot visits with LPR units may lead to an effect. Yet, most agencies currently have only one or two units to deploy at any given time (Lum et al. 2010). Or, perhaps if the data supporting LPR units were more expansive, more crime detection and prevention might be achieved. One

[12] International Association of Chiefs of Police (2007). Support for License Plate Reader Systems. Accessed May 24, 2010 from the International Association of Chiefs of Police website: http://www.iacp.org/resolution/index.cfm?fa=dis_public_view&resolution_id=324&CFID=9952799&CFTOKEN=30183528

[13] In a recent report by *USA Today*, a spokesperson for ELSAG, one of the major manufacturers of LPR systems, estimated that approximately 40 agencies in the DC metropolitan are using LPR systems.

might imagine many different offender or place-based datasets to which vehicle license plates might be linked, to increase the range of crimes of which LPR could deter, detect, or reduce. Further, the data collected from the LPR units themselves might be used in proactive ways to prevent crime. Lum et al. (2010) discusses a "continuum of uses" of LPR, including primary use for detecting auto thefts, directly linking to other databases, or proactively mining LPR data for crime prevention purposes. Yet, each of these uses carries various privacy and other legal concerns. And, there is still the real possibility that LPR is not an effective technology for police work.

However, our findings do not suggest that we should be resigned to using arrest and recovery rates as the measure of success of LPR. During the presentation of these findings at the 2010 Stockholm Symposium, an individual suggested that the non-significant findings simply reinforced the notion that the performance measure used for LPR should not be crime rates but rather arrests and license plates scanned. We disagree. Police scholarship has made significant inroads into moving police away from only considering reactive, police-initiated performance measures such as numbers of arrest. Indeed, arrest rates can increase with no effect on crime or calls for service. Rates of crime or calls for service could even increase during periods of more arrests. Further, one would be hard pressed to justify a $20,000 purchase of an LPR unit with an increase of a few arrests but without a decrease in crime (unless, perhaps, those arrests could be linked to a decrease in crime over the long term). We also disagree with the argument that promotes a "number of scans" or "number of positive hits" benchmark for successful deployment. Most obviously, an officer can obtain the same number of scans in one area compared to another, but with different positive hit rates.

Despite these limitations and the null findings, this experiment, with Taylor et al. (2011), are two of the first experimental evaluations of a police technology and their effects on crime. Surprisingly, there are only a few evaluations which focus on the effectiveness of LPR technology. However evaluations of technology effectiveness can lead to interesting findings about not only the utility of the technology, but also the nature of policing and police organizations.

References

Bailey, T., & Gatrell, A. (1995). *Interactive Spatial Data Analysis*. Harlow: Pearson.

Barclay, P., Buckley, J., Brantingham, P. L., Brantingham, P. J., & Whinn-Yates, T. (1995). Preventing auto theft in suburban Vancouver commuter lots: Effects of a bike patrol. In R. Clarke (Ed.), *Crime prevention studies* (Vol. 6). Monsey: Criminal Justice Press.

Boruch, R., De Moya, D., & Snyder, B. (2000). The importance of randomized field trials. *Crime and Delinquency, 46*(2), 156–180.

Braga, A., & Bond, B. J. (2008). Policing crime and disorder hot spots: A randomized controlled trial. *Criminology, 46*(3), 577–607.

Braga, A., Weisburd, D., Waring, E., Green Mazerolle, L., Spelman, W., & Gajewski, F. (1999). Problem-oriented policing in violent crime places: A randomized controlled experiment. *Criminology, 37*(3), 541–580.

Brantingham, P. J., & Brantingham, P. L. (Eds.). (1981). *Environmental criminology*. Beverly Hills: Sage.

Chan, J. (2003). Police and New Technologies. In T. Newburn (Ed.), *The Handbook of Policing*. Collompton: Willan.

Clarke, R., & Weisburd, D. (1994). Diffusion of Crime Control benefits: Observations on the reverse of displacement. In R. Clarke (Ed.), *Crime Prevention Studies Vol. 2* (pp. 165–183). Monsey: Willow Tree Press.
Cohen, Plecas, & McCormick (2007). *A report on the utility of the automated license plate recognition system in British Columbia*. Unpublished report
Copes, H. (1999). Routine activities and motor vehicle theft: A crime specific approach. *Journal of Crime and Justice, 22*(2), 125–146.
Durlauf, S. N., & Nagin, D. S. (2011). Overview of “Imprisonment and crime: Can both be reduced?”. *Criminology & Public Policy, 10*(1), 9–12.
Ericson, R. V., & Haggerty, K. D. (1997). *Policing the Risk Society*. Toronto: University of Toronto Press.
Felson, M., & Poulsen, E. (2003). Simple indicators of crime by time of day. *International Journal of Forecasting, 19*, 595–601.
Gardner, W., Mulvey, E., & Shaw, E. (1995). Regression analyses of counts and rates: Poisson, overdispersed poisson, and negative binomial models. *Psychological Bulletin, 118*(3), 392–404.
International Association of Chiefs of Police. (2009). *Privacy impact assessment report for the utilization of license plate readers*. Alexandria: International Association of Chiefs of Police.
Koper, C. (1995). Just enough police presence: Reducing crime and disorderly behavior by optimizing patrol time in crime hot spots. *Justice Quarterly, 12*(4), 649–672.
Koper, C., Taylor, B., & Kubu, B. (2009). *Law enforcement technology needs assessment: Future technologies to address the operational needs of law enforcement*. Washington, DC: Police Executive Research Forum.
Lu, Y. (2003). Getting away with the stolen vehicle: An investigation of journey-after-crime. *The Professional Geographer, 55*(4), 422–433.
Lu, Y., & Thill, J. (2003). Assessing the cluster correspondence between paired point locations. *Geographical Analysis, 35*(4), 290–309.
Lum, C. (2009). Translating police research into practice. *Ideas in American Policing, 11*, 1–16.
Lum, C. (2010). Gadgets for gathering evidence are not evidence of better policing. *Science Progress*, Accessed June 1, 2010 from the Science Progress website: http://www.scienceprogress.org/2010/02/police-technology/.
Lum, C., Koper, C. & Telep, C. (2009). The evidence-based policing Matrix. *Online Tool*. Located at http://gemini.gmu.edu/cebcp/matrix.html.
Lum, C., Merola, L., Hibdon, J., & Cave, B. (2010). *License Plate Recognition Technologies for Law Enforcement: An Outcome and Legitimacy Evaluation*. SPAWAR and National Institute of Justice. http://gemini.gmu.edu/cebcp/LPR_FINAL.pdf.
Lum, C., Koper, C., & Telep, C. (2011). The evidence-based policing Matrix. *Journal of Experimental Criminology, 7*(1), 3–26.
Maryland State Highway Authority (2005). *Evaluation of license plate recognition system*. Accessed November 11, 2009 from the American Association of State Highway and Transportation Officials website: http://www.transportation.org/sites/ssom/docs/LPR_report_part3.pdf.
Maxfield, M., & Clarke, R. V. (Eds.). (2004). *Understanding and preventing car theft* (Crime prevention studies, Vol. 17). Monsey: Criminal Justice Press.
Melbin, M. (1978). Night as frontier. *American Sociological Review, 43*(1), 3–22.
Nagin, D. S. (1998). Criminal deterrence research at the outset of the twenty-first century. *Crime and Justice, 23*, 1–42.
National Research Council (2004). *Fairness and effectiveness in policing: The evidence*. Committee to Review Research on Police Policy and Practices. W. Skogan & K. Frydl (eds.). Committee on Law and Justice, Division of Behavioral and Social Sciences and Education. Washington, DC: National Academies Press.
Home Office. (2007). *Police Standards Unit: Evaluation of Automatic Number Plate Recognition 2006/2007*. London: PA Consulting Group.
Ohio State Highway Patrol (2005). *Automatic plate reader technology*. Planning Services Section Research and Development.
PA Consulting Group. (2003). *Engaging criminality – Denying criminals the use of the road*. Great Britain. London, UK: PA Consulting Group.PA Consulting Group. (2006). Police Standards Unit: Thematic review of the use of automatic number plate recognition within police forces. London, UK: PA Consulting Group.
PA Consulting Group. (2004). *Driving crime down – Denying criminals the use of the road*. Great Britain, Home Office. Accessed July 21st, 2009 from http://police.homeoffice.gov.uk/news-and-publications/publication/operational-policing/Driving_Crime_Down_Denyin1.pdf?view=Binary.

Pierce, G., Spaar, S., & Briggs, L. (1988). *The character of police work: Strategic and tactical implications*. Boston: Center for Applied Social Research.
Rengert, G. (1997). Auto theft in central Philadelphia. In R. Homel (Ed.), *Policing for Prevention: Reducing Crime, Public Intoxication, and Injury* (pp. 199–220). Monsey: Criminal Justice Press.
Sherman, L. W. (1990). Police Crackdowns: Initial and Residual Deterrence. *Crime and Justice: A Review of Research, 12*, 1–48.
Sherman, L. W. (1998). *Evidence-based policing* (Ideas in American Police Series). Washington, DC: The Police Foundation.
Sherman, L. W., & Weisburd, D. (1995). General deterrent effects of police patrol in crime "hot spots": A randomized controlled trial. *Justice Quarterly, 12*(4), 626–648.
Sherman, L. W., Gartin, P., & Buerger, M. (1989). Hot spots of predatory crime: Routine activities and the criminology of place. *Criminology, 27*(1), 27–56.
Sherman, L. W., Gottfredson, D., MacKenzie, D. L., Eck, J., Reuter, P., & Bushway, S. (1997). *Preventing crime: What works, what doesn't, what's promising: A report to the United States Congress*. Washington, DC: National Institute of Justice.
Sherman, L. W., Farrington, D. P., Welsh, B. C., & MacKenzie, D. L. (2002). *Evidence-based crime prevention*. New York: Routledge.
Taylor, B., Koper, C., & Woods, D. (2011). *Combating auto theft in Arizona: A randomized experiment with license plate recognition technology. Final Report to the National Institute of Justice*. Washington, DC: Police Executive Research Forum.
Weisburd, D. (2000). Randomized experiments in criminal justice policy: Prospects and problems. *Crime and Delinquency, 46*(2), 181–193.
Weisburd, D. (2002). From criminals to criminal contexts: Reorienting criminal justice research and policy. *Advances in Criminological Theory, 10*, 197–216.
Weisburd, D. (2008). *Place-based policing. Series on Ideas in American policing*. Washington, DC: The Police Foundation.
Weisburd, D., & Eck, J. E. (2004). What can police do to reduce crime, disorder, and fear? *The Annals of the American Academy of Political and Social Science, 59*(1), 42–65.
Weisburd, D., & Green, L. (1995). Policing drug hot spots: The Jersey City Drug Market Analysis experiment. *Justice Quarterly, 12*(4), 711–735.
Weisburd, D., & Lum, C. (2005). The Diffusion of Computerized Crime Mapping in Policing: Linking Research and Practice. *Police Practice and Research: An International Journal, 6*(5), 419–434.
Weisburd, D., Bushway, S., Lum, C., & Yang, S. (2004). Trajectories of crime at places: A longitudinal study of street segments in the city of Seattle. *Criminology, 42*(2), 283–321.
Weisburd, D., Wyckoff, L., Ready, J., Eck, J., Hinkle, J., & Gajewski, F. (2006). Does Crime Just Move Around the Corner? A Controlled Study of Spatial Displacement and Diffusion of Crime Control Benefits. *Criminology, 44*(3), 549–592.
Weisburd, D., Bernasco, W., & Bruinsma, G. (Eds.). (2009). *Putting crime in its place*. New York: Springer.

Cynthia Lum is an associate professor in the Department of Criminology, Law & Society at George Mason University, and Deputy Director of its Center for Evidence-Based Crime Policy.

Julie Hibdon is a research associate for the Center for Evidence-Based Crime Policy at George Mason University.

Breanne Cave is a doctoral candidate in the Department of Criminology, Law & Society at George Mason University, and a research assistant for its Center for Evidence-Based Crime Policy.

Christopher S. Koper is an associate professor in the Department of Criminology, Law & Society at George Mason University, and a Senior Fellow of its Center for Evidence-Based Crime Policy.

Linda Merola is an assistant professor in the Department of Criminology, Law & Society at George Mason University, and a research affiliate of its Center for Evidence-Based Crime Policy.