Article

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Practice-Based Research: Ex Post Facto Evaluation of Evidence-Based Police Practices Implemented in Residential Burglary Micro-Time Hot Spots

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Abstract

Background: Police agencies around the country are implementing various strategies to reduce crime in their communities that need to be evaluated. These strategies are often based on systematic crime analysis and are focused on crime occurring in hot spots, which are areas of disproportionate amounts of crime. **Objective:** This article takes a practice-based research approach to evaluate whether evidence-based police strategies implemented by one police agency as its normal everyday crime reduction practice are effective in reducing residential burglary incidents in micro-time hot spots. **Research Design:** A quasi-experimental ex post facto

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design is employed using 5 years of data from one police agency that has institutionalized the identification and response to micro-time hot spots into its day-to-day practices. Propensity score matching is used to match 54 pairs of micro-time hot spots using logistic regression to compute the propensity scores and greedy 1 to 1 matching with a caliper width of 0.5 of the standard deviation of the logit to match the cases. **Results:** Independent *t*-tests show that tactical police response to micro-time hot spots can lead to significant reductions in residential burglary incidents without the spatial displacement of crime. **Conclusion:** Tactical police responses that seek to achieve short-term reductions in crime appear to be well suited for micro-time hot spots since they are, by nature, short term. Importantly, the conclusions are based on the evaluation of an agency's systematic implementation of the evidence-based practices as its normal practices and not for the sake of research.

Keywords
practice-based research, police, propensity scores, residential burglary, micro-time hot spots, evidence-based, crime reduction

Introduction

Evidence-based policing is "the use of the best available research on the outcomes of police work to implement guidelines and evaluate agencies, units, and officers" (Sherman, 1998, p. 3). Over the past 30 years, there has been a great amount of research using rigorous methods (i.e., experiments and quasi-experiments) that provide the foundation for evidence-based policing practices (Telep & Weisburd, 2012). However, determining that police strategies are effective through experiments designed by researchers and implemented with external funding does not necessarily mean that they will also be effective once implemented into the normal, everyday practices of a police agency. Thus, as evidence-based police practices are implemented into police departments, it is also important to determine through research whether and how these practices work in a real-world context. This latter type of research, called "practice-based research" (Boba, 2010), is complementary to evidence-based policing and is just as important to determine which crime reduction strategies are realistic and sustainable.

Over the past decade, the field of psychiatry has recognized this need as well. Marginson et al. (2000) assert that although randomized control trials are important for testing treatments, results of meta-analyses of that research reveal that there is a lack of evidence instead of evidence for or against a particular treatment. They argue that to complement these experimental studies, evidence based on good quality data collected from routine psychiatry practice may provide direction for implementation of treatments as well. In other words, research conducted in the environment in which the therapy occurs as well as in an academic clinical setting is imperative (Hellerstein, 2008; Marginson et al., 2000).

This study falls into the realm of practice-based research on policing in that it evaluates one police agency's standardized implementation of evidence-based crime reduction practices over 5 years. This provides a unique opportunity for practice-based research in that the agency did not implement the strategies with external funding or specifically for the research but did so with its current resources as part of its "way of doing business." Using the same methodology that examined theft from vehicle crime published in the *Journal of Quantitative Criminology* (Santos & Santos, 2015a), we employ a quasi-experimental ex post facto design to evaluate the effectiveness of tactical policing strategies implemented in micro-time hot spots of residential burglary.

For this evaluation, we use 5 years of data from one police agency that has institutionalized the identification and response to micro-time hot spots and determine the treatment and comparison groups of the quasi-experiment by matching cases on individual propensity scores. We then use independent *t*-tests to determine both the impact of evidence-based police response on residential burglary in the micro-time hot spots and whether spatial displacement of crime occurs as a result of the police response.

Evidence-Based Unit of Response: Micro-Time Hot Spot

In this study, micro-time hot spots are a subset of what police crime analysts call, "crime patterns" (Santos, 2013a). According to the International Association of Crime Analysts (IACA; 2011), a crime pattern is:

> . . . a group of two or more crimes reported to or discovered by police that are unique because they meet each of the following conditions: 1. They share at least one commonality in the type of crime; behavior of the offenders or victims; characteristics of the offender(s), victims, or targets; property taken; or the locations of occurrence; 2. There is no known relationship between victim(s) and offender(s) (i.e., stranger-on-stranger crime); 3. The shared commonalities make the set of crimes notable and distinct from other criminal activity occurring within the same general date range; 4. The criminal activity

> is typically of limited duration, ranging from weeks to months in length; and 5. The set of related crimes is treated as one unit of analysis and is addressed through focused police efforts and tactics. (p. 1)

We offer a definition of a micro-time hot spot as the emergence of several closely related crimes within a few minutes travel distance from one another (i.e., micro-place) that occurs within a relatively short period of time (i.e., micro-time)—a crime "flare-up" (Santos & Santos, 2015a). Since there are a variety of types of crime patterns (e.g., series, sprees, hot settings, and hot products; IACA, 2011), we distinguish the micro-time hot spot as a specific type of crime pattern as well as differentiate it from traditional long-term hot spots on which most evidence-based police researcher is focused (Braga, Papachristos, & Hureau, 2014).

Research has established that near-repeat victimization, which is the premise that nonvictimized places *near* places that have been victimized are much more likely to be victimized, exists for residential burglary (Bowers & Johnson, 2005; Johnson & Bowers, 2004; Townsley, Homel, & Chaseling, 2003) and has been shown to occur rapidly (Johnson, Summers, & Pease, 2007, 2009). Specifically, a study by Johnson and Bowers (2004) showed that residential burglaries clustered in time and space, not because of pure repeat victimization but primarily because of the near-repeat victimization. Bowers and Johnson (2005) found that houses next to a burgled home were at a substantially higher risk, that most incidents occurred within 1 week of the initial burglary, and that houses located on the same side of the street of an initial burglary were 1.5 times more likely to be burglarized than houses opposite side of the street.

Research investigating why near-repeat victimization occurs shows that the increased risk is caused by offenders returning to the area of a prior successful burglary. If the previous house is still vulnerable, offenders will revictimize it, but if that house has been hardened (e.g., posted alarm signs in the front yard, locked windows, and doors), the offenders select another house or they seek similar property in a nearby house (Coupe & Blake, 2006). Studies conducted in the Netherlands (Bernasco, 2008) and the United Kingdom (Johnson et al., 2009) show that around 98% of repeat burglaries that occur within a week are caused by returning offenders.

Johnson, Lab, and Bowers (2008) found that there are short-term clusters of crime within and separate than long-term clusters. Examining 6 months of residential burglary and theft from vehicle data in 2-week intervals, they found that "some areas that experience a high cumulative risk of victimization of the six month period had stable time series . . . and other areas with equally high cumulative risks experience a much less consistent pattern of risk over time" (p. 39). That is, in some areas, most 2-week periods had little risk of victimization, but there were 2-week periods here and there with very high risk. Thus, simply examining crime for long-term hot spots can (1) create the "illusion" (Johnson, Lab, & Bowers, 2008) that a stable hot spot exists when it does not and (2) ignore crime flare-ups that occur in isolation.

Evidence-Based Police Response to Micro-Time Hot Spots

Important in translating the evidence into practice is that if different types of hot spots do, in fact, exist, they will require different types of responses. That is, resolving a long-term hot spot would benefit most from identifying long-term solutions such as changing its criminogenic characteristics and the built environment. However, tactical police response seems more appropriate to micro-time hot spots that flare-up, since there is not enough time for long-term solutions to be implemented (Johnson et al., 2008).

In this study, the responses implemented by this police agency are those that have been shown to be effective through long-term hot spots policing research and generally include (1) increased patrol and field contacts, (2) proactive arrests, and (3) crime prevention contacts (Braga et al., 2014). In addition, they are strategies commonly used in police agencies around the United States as well as in the United Kingdom and Australia (Weisburd, Telep, & Braga, 2010). Weisburd and Lum (2005) found in a sample of 125 large U.S. police agencies (with 100 or more officers) that 66% reported using the hot spots policing approach. A survey conducted by Police Executive Research Forum (2008) found that in a sample of 192 U.S. police agencies, 74% used hot spots enforcement to address violent crime.

The Campbell Collaboration systematic review of hot spots policing studies has shown that this approach is effective in reducing crime (Braga et al., 2014). Thus, it is considered an "evidence-based approach" (Lum & Koper, 2011). Closer examination of these results as well as findings from less rigorous hot spots studies shows that the decreases in crime and calls for police service are primarily short term (Braga & Weisburd, 2010). The long-term hot spot studies that show a decrease in crime also show that the effects tend to dissipate quickly after the intervention and are not sustained (Braga et al., 2014). Thus, it appears as though these particular tactical responses to hot spots have a short-term effect, which supports the notion that these responses might be better suited as response for "crime flare-ups" since they are also short term.

The Current Study

This evaluation examines micro-time hot spots of residential burglary, where previous hot spots studies have examined crime and/or disorder very generally or violent crime and/or narcotics long-term hot spots specifically (Braga et al., 2014). The examination of residential burglary micro-time hot spots is important because property crime is the most frequent crime in most jurisdictions (Federal Bureau of Investigation, 2014); is the concern of police agencies, large and small and urban and rural; and has not been studied in this way.

The data for this study come from the Port St. Lucie, FL, Police Department which is located in southeast Florida along the coast. The city has grown significantly over the last 20 years with a population of about 55,000 in 1990 to nearly 170,000 in 2014. Its UCR Part I Crime Rate per 100,000 in 2013 was 1,627. Over the last 10 years, number of authorized sworn officer positions peaked in 2008 at 262, but due to the recent economic downturn, the agency currently has 224 authorized sworn positions as of December 2014. Because the city is a suburban bedroom community with no major malls or large business plazas, the majority of thefts from vehicles occur in residential neighborhoods.

Micro-time hot spots represent the short-term units of response for the police department's crime reduction efforts. Importantly, none of the agency's evidence-based efforts (i.e., analysis or responses) are employed as "extra" resources or through the use of overtime, making this distinct opportunity for practice-based research.[1]

To facilitate police response, trained crime analysts identify micro-time hot spots on a daily basis through an established crime analysis methodology (Gwinn, Bruce, Cooper, & Hick, 2008; Santos, 2013a), and each division within the agency contributes to the response. The tactical responses are implemented as quickly as possible when a micro-time hot spot is identified. In addition, all police vehicles are equipped with computers, and officers are mandated to capture any responses to micro-time hot spots via an intranet system. Finally, the agency conducts accountability meetings on both a weekly and monthly basis that ensure the micro-time hot spots are being identified and the responses are being implemented.

Unit of Analysis and Data

Operationalization of the micro-time hot spot by the police department was based on standard crime analysis practice for identifying crime patterns (Santos 2012), the geography of the jurisdiction, the frequency of theft from vehicle crime in the city as well as what is realistic for police response with the resources available. The agency's criteria were (1) two or more residential burglaries, (2) occurring from 1 to 14 days of another, (3) within a 0.5-mile radius or 0.79 square miles.

The maximum radius was chosen by the police department based on the city's size (i.e., over 110 square miles), the nature of zoning (i.e., most lots are 1/4 acre with single family homes), and what they felt was reasonable for police officers to respond to within a shift and their geographic areas of responsibility. Note that most of the micro-time hot spots were smaller than the maximum with the average examined in this study being a 0.30 radius or 0.28 square miles. In addition, we are careful to describe exactly how micro-time hot spots were identified, since the process was practical, qualitative, and different than the research on long-term hot spots.

The crime analysts made subjective decisions about which crimes were related in order to provide police with the best information possible for their responses and did not automatically relate individual crimes together because they occur in the same area within a certain time period. The crime analysts used a long-standing, standardized qualitative methodology for identifying the micro-time hot spots (Santos 2012) and considered date and time, location, along with method of the crime (e.g., point of entry and method of entry), property taken, and only examined those crimes in which the offenders were strangers to the victims (Gwinn et al., 2008; Santos 2012). Importantly, environmental and geographic factors were also considered during the analysis.

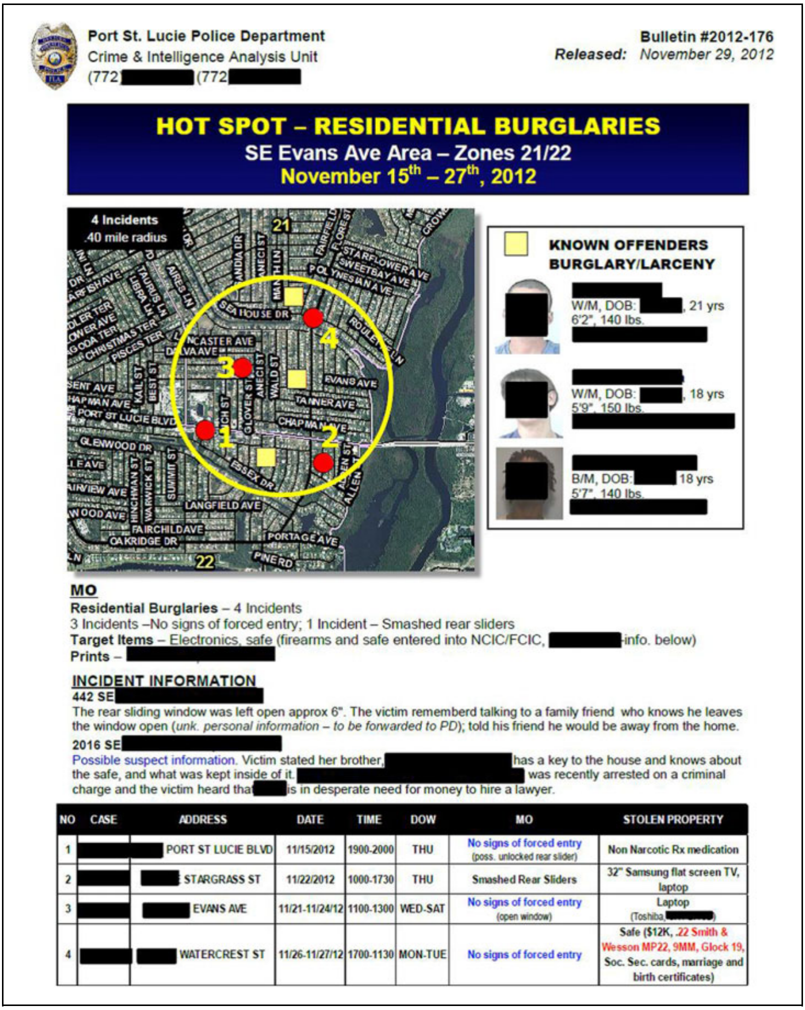
The following is an example of how the identification of micro-time hot spots occurred in practice. The crime analyst would map all residential burglaries in the last 14 days and manually look for incidents on the map that were within a 0.5-mile radius of one another. Once at least two residential burglaries were identified as proximate, the crime analyst read the narratives of the police reports to determine the details of the crimes, such as the time of day, day of week, the point of entry and method of entry, the property taken, and other qualitative factors (e.g., use of a pry bar, witnesses, and no forced entry). The crime analyst also looked closely on the map to determine whether the two crimes' geographic locations were separated by natural or man-made barriers that would make it less likely that the same offender(s) committed them.

Once a micro-time hot spot was identified, the crime analyst produced a one-page bulletin including information such as date, time, locations of the crimes, modus operandi (MO) and suspect information, known residential burglary offenders that live in micro-time hot spot, related field interview information, and whether evidence was collected at the scene (e.g., fingerprints and DNA). A map was included on the bulletin that illustrated the locations of the crimes, the field contacts, and residences of known offenders as well as the radius in which the crimes occurred. Figure 1 is an example of what was distributed to police personnel.

Importantly, the first bulletin only depicted the initial micro-time hot spot that would initiate the police response. The crime analysts tracked each micro-time hot spots until there were no additional crimes within 21 days of the last crime that occurred within a 0.50-mile radius in order to determine whether the micro-time hot spot was resolved and the responses could be stopped. If there were more crimes, an updated bulletin was produced and disseminated, which might depict a new radius. Unlike traditional long-term hot spots that are static once identified, micro-time hot spots are dynamic. Figure 2 illustrates how additional crimes are considered and whether they are added to the micro-time hot spot once it is identified.

The left map shows a micro-time hot spot at initial identification with two crimes within a 0.10-mile radius and within 4 days of one another (i.e., February 1st to February 5th). The middle map shows an update in which Crimes #3 and #4 are included because they are within a 0.25-mile radius of the mean center of the two original crimes with #3 occurring 2 days after #2 and #4 occurring 3 days after #4 (i.e., within 21 days). The right map shows how crime #6 is included because it falls inside the 0.25 radius of the other crimes and within 7 days of Crime #4, but that Crime #5 is not included even though it occurred before Crime #6 because it does not fall within 0.50 miles (the maximum based on the criteria) of the center of the other crimes. Finally, although #7 falls within the 0.25-mile radius of the micro-time hot spot, it occurred 25 days after #6 so is not part of the micro-time hot spot. Thus, the micro-time hot spot ends with five crimes occurring within a 0.25-mile radius in 16 days.

It is possible that a new micro-time hot spot could be formed around Crime #5 in terms of space and #7 in terms of time, but they would each have to meet the criteria of a new micro-time hot spot (i.e., 2 crimes within 0.50 miles and 14 days). In other words, once a crime is part of a micro-time



Port St. Lucie Police Department
Crime & Intelligence Analysis Unit
(772[redacted] (772[redacted]

Bulletin #2012-176
Released: *November 29, 2012*

HOT SPOT – RESIDENTIAL BURGLARIES
SE Evans Ave Area – Zones 21/22
November 15th – 27th, 2012

KNOWN OFFENDERS BURGLARY/LARCENY

[redacted]
W/M, DOB: [redacted], 21 yrs
6'2", 140 lbs.
[redacted]

[redacted]
W/M, DOB: [redacted], 18 yrs
5'9", 150 lbs.
[redacted]

[redacted]
B/M, DOB: [redacted] 18 yrs
5'7", 140 lbs.
[redacted]

MO
Residential Burglaries – 4 Incidents
3 Incidents –No signs of forced entry; 1 Incident – Smashed rear sliders
Target Items – Electronics, safe (firearms and safe entered into NCIC/FCIC, [redacted] info. below)
Prints – [redacted]

INCIDENT INFORMATION
442 SE [redacted]
The rear sliding window was left open approx 6". The victim rememberd talking to a family friend who knows he leaves the window open (*unk. personal information – to be forwarded to PD*); told his friend he would be away from the home.
2016 SE [redacted]
Possible suspect information. Victim stated her brother, [redacted] has a key to the house and knows about the safe, and what was kept inside of it. [redacted] was recently arrested on a criminal charge and the victim heard that [redacted] is in desperate need for money to hire a lawyer.

NO	CASE	ADDRESS	DATE	TIME	DOW	MO	STOLEN PROPERTY
1	[redacted]	PORT ST LUCIE BLVD	11/15/2012	1900-2000	THU	No signs of forced entry (poss. unlocked rear slider)	Non Narcotic Rx medication
2	[redacted]	[redacted] STARGRASS ST	11/22/2012	1000-1730	THU	Smashed Rear Sliders	32" Samsung flat screen TV, laptop
3	[redacted]	[redacted] EVANS AVE	11/21-11/24/12	1100-1300	WED-SAT	No signs of forced entry (open window)	Laptop (Toshiba, [redacted])
4	[redacted]	[redacted] WATERCREST ST	11/26-11/27/12	1700-1130	MON-TUE	No signs of forced entry	Safe ($12K, .22 Smith & Wesson MP22, 9MM, Glock 19, Soc. Sec. cards, marriage and birth certificates)

Figure 1. Micro-time hot spot bulletin.

hot spot, it cannot be part of a new one, and even though micro-time hot spots may be close to one another, they cannot overlap.

The same two analysts published all micro-time hot spot bulletins for the agency for the entire 5-year evaluation period following the guidelines that constitute a micro-time hot spot. Each bulletin was posted by the crime analyst into an intranet system. For those micro-time hot spots that were

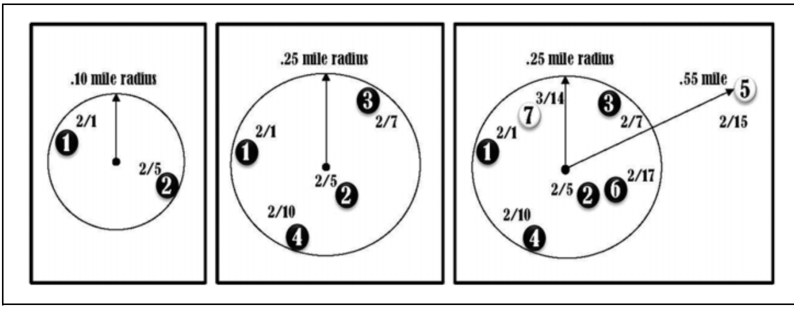


Figure 2. Illustration of the micro-time hot spot.

assigned a response, police personnel entered their response information in real time through the laptops in their police cars. The officers' name and date and time were automatically recorded, and the response information was entered into a free-text field.

As with most police departments, this agency had a policy for responding to individual residential burglaries. Therefore, all residential burglaries that were reported to the police over these 5 years received a response from the agency. The response included a patrol officer responding to the home, taking a report, and doing a preliminary investigation as well as detective follow-up when appropriate. In contrast, the responses tested in this study were specific tactical police responses that were directed at the micro-time hot spots as the unit of response not for individual crimes.

The tactical responses implemented in the micro-time hot spots fall into three categories including (1) directed patrol, (2) contacting potential victims, and (3) contacting known offenders. The directed patrol included officers being stationary or driving in the micro-time hot spot area for at least 15 min each time, but they could have been there for more or less time depending on the circumstance and level of resources and demand for service at the time. In some instances, directed patrol resulted in field interview cards, vehicle traffic stops, citations, and searches or contacts with potential victims.

The crime prevention unit contacted potential victims through a "Reverse-911" call facilitated through a system, which allowed the police department to call residents living in a micro-time hot spot and provided a tailored phone message about the crime that was occurring. The agency also used a volunteer response team that consisted of volunteers who drove around in marked vehicles, distribute tailored flyers about the crime happening in the micro-time hot spot area, and spoke to individual residents in person when possible. Lastly, when names and home addresses of known residential burglary offenders living in the micro-time hot spot were provided on the bulletins, detectives and officers made contact to determine whether the individuals were possible suspects for the crimes in the micro-time hot spot or to deter them from committing any or additional crime.

The agency's policy was that responses to each micro-time hot spot were implemented for 14 days after the last crime in the micro-time hot spot. However, the length of police response did not directly correspond with the analysts' time frame for monitoring (i.e., 21 days). This decision was based on the agency's resources and what was realistic to sustain. Importantly, this process included a continual review by the crime analysts and response by police that ended when there was a continual absence of any crimes for 21 days. The duration of the response was determined by the last date of the last response for a particular micro-time hot spot even if the responses had stopped sometime during the duration of the entire hot spot. Note that even in micro-time hot spots in which responses continued for 14 days, there could have been a day within that time period with no responses, since responses were implemented when resources were available.

For this evaluation, there were 223 residential burglary micro-time hot spots identified in the agency from 2008 to 2012 or about 45 per year. The original response database included 6,497 entries. After cleaning entries that were informational only or did not pertain to a response, there were 5,075 response entries. These responses were then aggregated to determine the total number and types of responses employed for each micro-time hot spot. Each entry was coded into one of the following categories: (1) directed patrol only (i.e., no additional contact), (2) directed patrol with additional activity (e.g., citizen contact and field interview), (3) known offender contact, (4) citizen contact by volunteers, or (5) reverse 911. All responses were counted as one response except "directed patrol with additional activity," which was assigned a value of 2 to take into account the additional activity (i.e., patrolling the area and contacting someone vs. just patrolling an area). To arrive at the final database, the micro-time hot spot bulletin data were merged with the aggregated police response data by bulletin number. What resulted was a database with 223 micro-time hot spots, 118 with response, and 105 without.

Control Variables

We selected the comparison group cases for the quasi-experimental design by computing propensity scores for each case and matching them to treatment cases. An important step in reducing bias in the matching process is including theoretically relevant covariates whenever possible (Rosenbaum & Rubin, 1985). It is impossible to account for all potential covariates that might differentiate micro-time hot spots, particularly, those related to the agency's policies for allocating response. Not being able to control for those unobservable factors with random assignment is the weakness of an ex post facto quasi-experimental design; however, we have included all the observed characteristics of the micro-time hot spots as captured on the bulletins as well as two characteristics that were created after the fact based on information on the bulletin—season and number of targets. In addition, in the Appendix, we present the results of a rigorous sensitivity analysis (i.e., RBOUNDS) that examines the potential effect of unobservable covariates as well when using propensity score matching. This following is a description of each covariate that was used and its theoretical justification for its inclusion.

- *Year:* Year in which the initial micro-time hot spot was identified. It is included as a predictor because the levels of overall crime varied by year in the 5 years of the evaluation. This variable is a proxy for the larger criminogenic environment of the city.
- *Season:* Based on the month in which the initial micro-time hot spot was identified, the months were coded: *January, February, and March* = 1; *April, May, and June* = 2; *July, August, and September* = 3; *October, November, and December* = 4. The season may impact the opportunities for crime. For example, in the summer months, juveniles might be more likely to commit residential burglaries since homes are empty and juveniles are not in school during the daytime.
- *District:* Location within the city where the micro-time hot spot occurred. The police department separates the city into four districts. The nature of housing and commercial businesses in each of the districts is somewhat different. For example, one district is primarily residential and is somewhat denser than other districts with very little commercial property except along large roads. Another district is primarily residential, but many of the homes are located in gated communities that limit access and reduce opportunities for crime.
- *Radius:* Radius of the crimes (in miles) in the initial micro-time hot spot. On each bulletin, a circle on the map encompassed all the crimes in the micro-time hot spot, which is a proxy for the area in which police responses could be implemented. In fact, the agency's stated policy is that officers are to patrol the area within the radius.

- *Density of potential targets:* This variable was created using aerial maps to count the parcels designated as single family homes within the radius as well as each multifamily home. This variable accounts for the specific differences in the number of potential residential targets for each micro-time hot spot.
- *Initial number of crimes:* Number of crimes when the micro-time hot spot is first identified. By the agency's policy, each micro-time hot spots has at least 2 crimes. However, many micro-time hot spots were initially identified with more than 2 crimes, thus this variable measures the relative intensity of the initial micro-time hot spot.
- *Time span:* Number of days between the first crime and the last crime in the initial micro-time hot spot. The time span provides an idea of the temporal scope of the micro-time hot spot when it was identified.
- *Number of known offenders:* Number of known residential burglary offenders who currently live within the radius. Crime analysts provided these on the bulletin as part of the agency's evidence-based police response. Research on short-term clustering of crime finds burglars are more likely to commit crimes relatively close to where they live (Bernasco, 2010).

Treatment Variable

The response data are used for two purposes in this analysis. First, the amount of response in each micro-time hot spot is used to select the micro-time hot spots that received treatment for the propensity score matching process. Second, a binary variable is used as the dependent variable in the logistic regression, which computed the propensity scores for each case with a value of 1 for treatment and 0 for no treatment. This evaluation does not disentangle the specific effect of the amount and type of response in the micro-time hot spots because it is a practice-based study examining a police department's real crime reduction strategy, which is a combination of strategies implemented together. As noted earlier, the combination of responses that were employed collectively were mandated by the agency's system of response and were based on the available resources and "real-time" decisions made by patrol managers. Importantly, this research is not able to fill the current recognized gap in the research on individual and specific police responses (Sorg, Wood, Groff, & Ratcliffe, 2014) because its purpose is to evaluate the normal everyday practice of one agency.

Outcome Variable: Residential Burglary Incidents

The dependent variable is the number of residential burglary incidents occurring after the micro-time hot spot was identified—Crime at "Time 2." All micro-time hot spots eventually cool down and resolve (i.e., stop or end) on their own whether or not a police response is implemented. Thus, this measure is the number of crimes that occurred in the micro-time hot spot after a response was or *could have been* employed by police (i.e., crimes after the initial bulletin was published).

Crime at "Time 1" or the covariate, "initial number of crimes," represents crimes that makeup the micro-time hot spot when it was initially identified by the crime analyst but before a response could have taken place. This variable was used in the propensity score matching, but it is not used as the baseline for the amount of crime expected after the response was implemented. That is, because these are acute clusters of crime, they are not identified because they have a disproportionate amount of crime in comparison to other areas as long-term hot spots are (Braga et al., 2014), but crime at Time 1 is based on the agency's criteria that denote a minimum number of crimes (i.e., at least 2 crimes). In addition, the goal of the analysis of micro-time hot spots is to identify them when they have the fewest numbers of crime, so that responses can be implemented immediately. In other words, analysts do not wait for crime for a "disproportionate" level of crime before they identify the micro-time hot spot. Thus, the amount of crime in the initial micro-time hot spot does not represent a "normal" amount of crime in that area but is merely the amount of crime in the micro-time hot spot, as it is identified, again, based on the agency's minimum criteria. Thus, the relative difference in crime at Time 1 and at Time 2 is not a meaningful measure for determining the impact of the response nor is "regression of the mean" of crime at Time 2 to Time 1 a factor in the analysis.

Finally, crime at Time 2 is not measured with a static amount of time after the response was implemented because of the way in which the agency defines the resolution of a micro-time hot spot. Crime at Time 2 is the number of crimes that occurred until there were no more crimes within 21 days from the last crime that occurred in the micro-time hot spot. Thus, the actual time period at Time 2 varied across micro-time hot spots based on how long it took each micro-time hot spot to "cool off" (i.e., the absence of any additional crime for 21 days).

Outcome Variable: Spatial Displacement of Crime

In long-term hot spots studies that examined spatial displacement of crime (see, e.g., Braga et al., 2014), researchers measured spatial displacement as the amount of crime occurring in about a two-block catchment area around the hot spots area within the response period. Using a relatively similar distance, the dependent variable for spatial displacement was the amount of crime within a 0.2-mile catchment area around the initial micro-time hot spot radius. The agency responded for a minimum of 14 days after the last crime in the last update of a micro-time hot spot, so the period examined here is from the initial date of the first police response until 14 days after the last crime in the last update.

Quasi-Experiment: Group Selection

Treatment group. Due to constraints and variation in resources over the 5 years of the evaluation, although the crime analysts consistently identified all micro-time hot spots occurring in the city, the agency did not respond to every micro-time hot spot that was published nor did it respond with equal amounts of response each time. That is, as micro-time hot spots were identified and distributed, they would automatically be assigned for response if the resources were there. Once managers reached a point where resources were not available to respond, any subsequent hot spots did not receive a response until resources became available again (i.e., existing responses were closed and finished).

Because there were more micro-time hot spots with response (118) than without response (105), it was necessary to reduce the number with response for the matching process since matching more than one comparison case to each treatment case is not as sound as a one-to-one match (Thoemmes & Kim, 2011). More importantly, the goal here was to evaluate the police department's "best practices," so instead of including micro-time hot spots with a wide variation in response, we selected treatment cases that were homogenous in that they received a relatively high level of police response to reflect the police department's ideal response strategy.

To identify these cases, the 118 micro-time hot spots with response were sorted in descending frequency by the number of responses per day (i.e., number of aggregated responses divided by the number of days of the response). The top 65 cases were retained for matching based on the natural breaks of the distribution. For all 118 micro-time hot spots, the minimum value for responses per day was 1.05 with a maximum of 8.46. The mean was 4.12 with a standard deviation (*SD*) of 2.14 and a median of 4.96. For the selected 65 cases, the distribution was more normal and clustered around the mean. The minimum was 3.94 responses per day with a maximum of 8.46. The mean (6.10) and median (5.96) were very close, and the

SD (0.81) clearly indicates the distribution was no longer skewed. The 53 cases that did have response but were not selected were totally removed from the analyses and were not used as comparison cases since they did have at least one response per day.

Comparison Group: Propensity Score Matching

We use propensity score analysis to determine the experimental groups (Rubin, 2006). The propensity score is a conditional probability that expresses how likely a participant is to receive "treatment" given certain observed theoretically important characteristics (Rosenbaum & Rubin, 1983) and is estimated with the eight control variables and the dummy treatment variable using the following logistic regression formula:

$$Ln\left[\frac{P(Z=1|X_1,...X_j)}{1-P(Z=1|X_1,...X_j)}\right]=\beta_0+\sum\nolimits_{j=1}^{p}\beta_jX_j,$$

where Z is the dummy (treatment) variable and X_1 to X_j are the eight covariates that were used to predict group membership of the treatment variable. Consequently, the predicted values of this equation are the estimated propensity scores for each case and the comparison group cases are matched to treatment group cases based on their individual propensity scores.[2]

We use standardized differences[3] as the key metric for assessing balance because this is the standard in both social science and medical research, is superior to significances tests (Thoemmes & Kim, 2011), and allows comparison of relative balance of variables measured in different units (e.g., year, month, and number of crimes; Austin, 2008b). A balanced Propensity Score Matching (PSM) model occurs when all the covariates, as well as their interaction and quadratic terms, have a standardized difference of less than .20 or, in other words, a bias level of less than 20% (Austin, 2009; Rosenbaum, 2002; Thoemmes & Kim, 2011).

The final model[4] was chosen because with the strictest caliper width, it yielded the most balance. When different models were performed in SPSS (Thoemmes, 2012), each covariate was taken out individually, and the final model was much better than the others without the known offender covariate. Selecting the model without this covariate was not simply a statistical choice but was a theoretical one as well. That is, although it is reasonable to expect that more known offenders residing within a micro-time hot spot may impact the likelihood of additional crimes in a micro-time hot spot, as it turns out, there was a high percentage of micro-time hot spots that did not have any known offenders on the bulletin (71.3%). In addition, 21.3% had one known offender on the bulletin, 6.5% had two, and 0.9% had three. This indicates that there were not many known residential burglary offenders living in the areas of these micro-time hot spots, which reduced the potential effect on that covariate having an impact on the dependent variable.

The result was that of the 65 cases in the treatment group, 11 cases were not matched, resulting in 54 pairs. Forty-one of the 105 comparison cases were not matched with 10 being discarded because they were outside the region of common support. To assess balance, Table 1 depicts the means for the propensity scores and each covariate for both the treatment and comparison groups, the *SD* for the comparison group (the denominator of the standardized differences measure), the individual standardized differences in percentage of the propensity score as well as the seven covariates for the groups *after* matching along with the absolute value average. The two final columns contain the results of independent *t*-tests[5] of the treatment and comparison groups after matching.

These results show that after matching, none of the covariates or the propensity score standardized differences was over 20%. In fact, all were under 6.7% with an average of 3.1%, and all covariates' standardized differences were lower after matching (e.g., not shown here, the mean for covariates before matching was 13.8%).

Testing Police Response Effectiveness

As a result of the matching process, the final database includes 108 cases, 54 cases in each group. Descriptive statistics for the key characteristics of the responses implemented in the treatment micro-time hot spots showed that on average, the police responded 95.99 times within 16.02 days or 6.06 responses per day. The medians for the number of responses (96.52), the number of days (16.00), and the response rate (6.03) were very close to their respective means, indicating normal distributions for each variable. In addition, the *SD*s, 10.45 for number of responses, 2.34 for the number of days, and 0.80 for response rate, are relatively small showing that for each variable, the micro-time hot spots were clustered closely around their means with very few outliers. Overall, these statistics indicate that response level in the 54 treatment micro-time hot spots was relatively homogeneous.

The following is the percentage breakdown by type of response. Note that in this computation, directed patrol with additional activity is not

Table 1. Balance Measures: Individual Standardized Differences and *t*-Tests.

Covariate	Treatment Mean ($N = 54$)	Comparison Mean ($N = 54$)	*SD* Comparison Group	Standardized Differences (%)	*t*-Statistic ($df = 106$)	*p* Value (Two-Tailed)
Propensity score	0.39	0.39	0.080	1.2	−.062	.95
Year	2010.11	2010.07	1.29	2.7	−.144	.89
Season	2.61	2.57	1.11	3.3	−.171	.86
District	2.37	2.43	0.92	−6.7	.325	.75
Radius	0.30	0.30	0.12	−3.5	.189	.85
Targets	919.41	914.70	370.64	1.1	−.06	.95
Crime	3.30	3.35	0.99	−5.4	.279	.78
Time span	7.19	7.15	3.61	0.9	−.051	.96
				Mean 3.1		

*$p \leq .001$.

weighted, but one directed patrol response entry with additional activity is weighted as one, thus the total *N* here is 4,303.

- 76.15%: Directed patrol only (i.e., no additional contact).
- 20.47%: Directed patrol with additional activity (e.g., citizen contact and field interview).
- 3.37%: Known offender contacts, citizen contact by volunteers, and Reverse 911.

Thus, nearly 97% of the agency's response to residential burglary micro-time hot spots were directed patrol activities with about one in four resulting in additional activity. In a quasi-experiment in which propensity scores are used, Schafer and Kang (2008) recommend using independent sample tests on matched data as are used in randomized data, which are also supported by Stuart (2008) and, in particular for social science research, by Thoemmes and Kim (2011). Therefore, we used independent *t*-tests to compare the mean crime of both the treatment and comparison groups at Time 2. The posttest comparison of the two experimental groups is key to determining the effect of police response for micro-time hot spots. However, long-term hot spot research also includes pre–post comparisons of each group or difference-in-difference paired *t*-tests (Telep, Mitchell, & Weisburd, 2014) since the history of the amount of crime in the long-term hot spot provides a baseline measurement for what is expected in the future. As noted earlier, the amount of crime in the initial micro-time hot spot does not represent the normal amount of crime to expect in the future since it is a short-term phenomenon, so conducting paired *t*-tests on crime Time 1 and Time 2 or on the difference in difference is not relevant and would not reveal meaningful results.

Table 2 compares the two groups based on three characteristics of the micro-time hot spots after they were resolved (Time 2): (1) the amount of crime that occurred after the initial identification, (2) the time span in days of those crimes, and (3) the final radius of the micro-time hot spot. The comparisons of the treatment and comparison groups for these three variables at Time 1 are shown in Table 1, and none of those differences was significant since their similarity was required of the propensity score matching process.

The comparison of crime at Time 2 is the test of the response effectiveness. The table shows that the average crime at Time 2 for the treatment group was 1.04 with a *SD* of 1.01 and for the comparison group was 2.19 with a *SD* of 1.68. The *SD*s indicate that the treatment group had more variation than the comparison group since its *SD* is relatively larger. However,

Table 2. Independent *t*-tests for Treatment Effectiveness.

Measure at Time 2	Treatment Mean (*SD*)	Comparison Mean (*SD*)	Mean Difference	*SE* Difference	*t*-Statistic	*df* (*N*)
Crime	1.04 (1.01)	2.19 (1.68)	1.148	0.267	4.300*	106 (54)
Time span	5.52 (5.35)	13.20 (7.97)	7.680	1.307	5.882*	106 (54)
Radius	0.32 (.13)	0.35 (.12)	0.348	0.025	1.418	106 (54)

*$p \leq .001$.

the mean difference between the groups of 1.148 was statistically significant and that the difference is in the predicted direction in that the treatment group's mean is significantly lower. These findings suggest that police response to residential burglary micro-time hot spots is effective and resulted in 1.15 fewer crimes per micro-time hot spot.

The average time span for the treatment group was 5.52 days in which the crime occurred and for the comparison group was 13.20 days. Similar to crime at Time 2, the *SD* for the treatment group was relatively larger indicating more variation than the control group. Yet, similar to crime, micro-time hot spots with response had significantly shorter times spans at Time 2. Thus, the micro-time hot spots that did not receive police response both lasted longer and had more crime incidents. It is an expected result that the micro-time hot spots lasted longer when there were more crimes because the actual time period at Time 2 varied across micro-time hot spots based on how long it took each micro-time hot spot to cool off (i.e., the absence of any additional crime for 21 days). The test of the final radii of micro-time hot spots of the two groups indicates that the means are not significantly different (p value $=$ .159) and the *SD*s are similar as well.

In a quasi-experiment that uses propensity score matching, even one that uses a high number of coefficients to accomplish matching, there is the possibility that the observed characteristics are not adequate for developing a robust model of equivalence and that unobserved characteristics result in a hidden bias making the results questionable. Rosenbaum (2002) developed a sensitivity test, commonly called "Rosenbaum bounds," to provide a specific statement about the magnitude of hidden bias. The Appendix shows a table with the results of the RBOUNDS test, which indicate that there is not an issue with hidden bias in the analysis.[6]

Finally, the spatial displacement variable reflects the amount of crime occurring within a 0.2-mile catchment area around the initial radius within 14 days of the last crime. In the treatment and comparison groups, four (7.4%) and six (11.1%) micro-time hot spots had at least one crime in the catchment area, respectively. The independent t-test of the two groups confirms that these amounts are not significantly different. The means for the number of crimes in the catchment area are 0.07 for the treatment and 0.11 for the comparison group. They yielded a t-value of $-.659$ and a p value of .511. Thus, these findings show that there was no spatial displacement of crime as a result of the police response.

Discussion and Conclusion

Our results show that tactical police response in micro-time hot spots leads to significant reductions in residential burglary without spatial displacement of crime in one jurisdiction. Using a practice-based approach by evaluating an agency's standardized crime reduction efforts over 5 years, we found that when police responded with about six responses per day and for between 2 and 3 weeks, there was around one less residential burglary in a micro-time hot spot. Overall, the micro-time hot spots with police response were resolved in half the time than those without a response (i.e., 5 vs. 13 days). In both groups, crimes occurring after the initial micro-time hot spots tended to be spatially clustered very close to the original crimes. Finally, we found no spatial displacement of crime after the response.

To translate the findings to real reductions in crime, the mean difference in crime between those micro-time hot spots and those without is divided by the total amount of crime in micro-time hot spots without response. Doing this produces the percentage of reduction in crime resulting from the police response. From Tables 1 and 2, the average crime in micro-time hot spots without response was 5.54 crimes (i.e., average crimes at Time 1 [3.35] plus the average at Time 2 [2.19]). Those micro-time hot spots with response had 1.15 significantly fewer crimes at Time 2; therefore, there was a 20.76% reduction (1.15 divided by 5.54) in crime when a police response was implemented.

In terms of place-based police response, day-to-day deployment of tactical police resources requires a more precise understanding of where residential burglaries just occurred and where they are most likely to happen in the next few days. Analysis of long-term hot spots does not direct resources at such an immediate level. Thus, we believe that our results also open both practice and research to the idea that tactical responses are better suited for short-term clusters of crime (i.e., micro-time hot spots). In fact, based on the culmination of research of long-term hot spots policing as well as problem-oriented policing and "pulling levers," Telep and Weisburd (2012) seem to concur with us when they argue that the most promise for reducing crime in long-term hot spots is in taking a multifaceted problem-solving approach in which police tailor their responses to the underlying causes of the problem versus using only tactical approaches such as directed patrol.

We maintain that police response to clusters of residential burglaries that concentrate quickly and for short periods of time is equally important as responding to crime in long-term stable hot spots. When those long-term hot spots experience crime flare-ups within them, it is an ideal time to initiate a tactical response. Doing so over a long period of time could essentially eliminate the long-term hot spot. A cursory look at this agency's micro-time hot spots of residential burglary over the 5 years showed that most of the micro-time hot spots occurred outside of the city's long-term hot spots (i.e., no overlap). Also, in areas where repeated micro-time hot spots did occur, there were long periods of time between them (i.e., months of cooling off between each micro-time hot spot). Thus, developing long-term solutions that address root causes of crime in the long-term hot spots while, at the same time, implementing tactical responses in the short-term flare-ups of residential burglary, seems to be a more efficient use of resources and a comprehensive approach for more effective crime reduction efforts overall.

Another practical implication is that responding to micro-time hot spots can be a way for police to increase their clearance rates and arrest offenders for these crimes. Investigations of property crime, specifically residential burglary, consistently result in low clearance rates of around 15% (FBI, 2014). Research shows residential burglaries that cluster in space over a short time are often committed by the same offenders. As noted earlier, Bernasco (2008) and Johnson, Summers, and Pease (2009) found that most near repeat burglaries that occur within a week are caused by returning offenders, and we infer that micro-time hot spots are also likely committed by the same offenders. Importantly, in practice, most residential burglaries are not assigned for investigation because there is little to no evidence, and the solvability for the crime is low. Consequently, if detectives look at all crimes in a micro-time hot spot together, when an arrest is made for one crime, they might determine if those other crimes in the micro-time hot spot can be linked to that offender. A consistent use of micro-time hot spots for investigations could arguably lead to a higher clearance rate for those targeted crimes.

Evidence-based police research has shown that implementing tactical responses in long-term hot spots is effective (Braga et al., 2014). While this is only one study, it has shown that a police department systematically employing these strategies for short-term hot spots is also effective. As practice-based research, these findings now provide some evidence for a common recommendation made by crime analysis researchers (Santos, 2012) and practitioner organizations (IACA, 2011) that police should identify and respond to crime patterns as standard practice. Police executives often debate about whether to expend resources for crime analysts as well as what they should spend their time doing (Santos, 2014). These findings suggest that police agencies would be spending their resources to hire crime analysts in order to systematically identify and respond to micro-time hot spots.

Despite our quasi-experimental methods and significant findings, the key limitation of this study and practice-based research is generalizability of the findings because it is a study of one agency with a unique crime reduction strategy. In addition, while a quasi-experimental design using propensity score matching is a solid methodology, it is not as rigorous as an experimental design and does not account for unanticipated influences. Because of this, our findings should be interpreted with caution, and we recommend other studies duplicate our analysis and improve upon it through more rigorous methodology.

The approach of this study was to test the implementation of tactical police response as part of normal everyday crime reduction practice was effective for reducing crime in micro-time hot spots. As an ex post facto study, we did not dictate how the micro-time hot spots were identified by the crime analysts or the response protocol. In Note #1, the agency received a prestigious award from International Association of Chiefs of Police in 2008 for the implementation of these evidence-based practices, and this study is one of the first that evaluates the implementation. The sustained implementation of responses to micro-time hot spots over 5 years has provided a unique opportunity for a rigorous practice-based study, and our results show that not only can these evidence-based strategies be successfully integrated into police practice, they also appear to have an impact on crime.

Finally, we do not assert that the practice-based approach replace the evidence-based approach, to the contrary, they should supplement one another. Just as we rely on triangulation of methods and multiple studies to verify a practice to be considered "evidence based," the same standards should be used for practice-based research. We hope that as evidence-based practices begin to be institutionalized into everyday police practice, rigorous practice-based policing research will also expand and begin establishing systematic findings as well.

Appendix

Table A1. Rosenbaum Bounds Test for Sensitivity.

Γ	p Critical	Hidden Bias Equivalent
1.00	.000022	−1.00
1.10	.000071	−1.00
1.20	.000191	−1.00
1.30	.000442	−1.00
1.40	.000903	−1.00
1.50	.001677	−1.00
1.60	.002876	−1.00
1.70	.007501	−1.00
1.80	.007036	−0.50
1.90	.010229	−0.50
2.00	.014304	−0.50
2.10	.019344	−0.50
2.20	.025413	−0.50
2.30	.032557	−0.50
2.40	.040800	−0.50
2.45	.045337	−0.50
2.50	.050148	−0.50

Note. $N = 54$.

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Notes

1. The agency employs stratified policing as its organizational framework for implementing evidence-based crime reduction strategies into the police organization's day-to-day practices by providing actionable crime analysis products and a foundation for the accountability of problem solving through a structured set of meetings (Santos & Santos, 2015b). The Port St. Lucie Police Department's success has been documented by a process and impact evaluation (Santos, 2013b) and has received a prestigious policing award, the International Association of Chiefs of Police Law Enforcement Research Award (International Association of Chiefs of Police, 2010).

2. All matching parameters are based on the recommendations made by Thoemmes and Kim (2011) in their meta-analysis of 86 social science research articles using propensity score matching published from 2003 to 2009 from psychology, education, criminology (11.6%), and public health.
3. Standardized mean differences are computed in this analysis as the mean difference between the treatment and comparison groups divided by the *SD* of the comparison group. This figure is then multiplied by 100 to come to a percentage bias figure as is used in other criminological studies (see, e.g., Braga et al., 2012).
4. As recommended by Rosenbaum and Rubin (1985), many different models with a variety of parameters were performed to determine the most robust model. All of the models used greedy matching and cases were eliminated that fell outside the regions of common support for both groups. Different combinations of the following were tested in the models: matching ratios (1 to 1 and 1 to 2 matching), replacement or no replacement and caliper widths (0.20, 0.10, and 0.05 of the *SD* of the logit), and removing each covariate from the model separately. For the sake of space, only the final model that was used to select the comparison cases is discussed.
5. The use of significance tests to determine the balance of PSM is common in the social science literature, yet key statisticians (Austin, 2008a; Thoemmes & Kim, 2011) recommend against using these tests because in some cases, nonsignificant results can emerge out of simply reducing the sample size, so these results could imply balance which may not have actually been achieved. However, for the sake of comparison to other criminological studies, independent *t*-tests are presented in Table 1 and show that none of the covariates was significantly different between the treatment and comparison groups after matching with the *p* values nearly all in the upper quartile.
6. Rosenbaum's method uses the sensitivity parameter Γ that indicates the departure from random assignment of treatment. In a randomized experiment $\Gamma = 1$ indicating there is no bias, where in a nonrandom study, if $\Gamma = 2$, and the cases have been matched on observed characteristics, then one might be twice as likely as the other to receive treatment because of an unobserved characteristics (Rosenbaum, 2002). Because the values of Γ, unobserved characteristics, are unknown, the sensitivity test looks at incremental values of Γ to see their effects. The Appendix table illustrates the results from the RBOUNDS program in STATA Version 13, which uses Rosenbaum's tests of sensitivity (Gangl, 2004). Stata output provides the maximum and minimum *p* values using Wilcoxon's signed ranks test and the Hodges–Lehmann point and interval estimates. Table A1 shows only the upper bound *p* values and point estimates. The lower bounds are not discussed here because they favor treatment and in most instances, this is not interesting because the findings indicate whether the bias

favors the comparison group, which means the results of the treatment would be even stronger than they appear. The first row shows $\Gamma = 1$, that is, no confounding bias. Each line below presents alternative values for Γ from 1 to 2 in increments of .1 except at 2.45. In the table, where Γ is between 2.45 and 2.50, the significance level exceeds .05, thus to explain away the observed characteristics and the possibility of response, a hidden bias would need to increase the odds of response by more than a factor of $\Gamma = 2.45$. This is a relatively large Γ value. Having controlled for observed bias with propensity score matching, an unobserved confounding variable would have to increase the likelihood of selection by nearly 245% and simultaneously offset the treatment estimate. In addition, interpretation of the hidden bias equivalent (see Braga, Hureau, & Papachristos, 2012 for a similar interpretation) shows that the critical level of 2.45 is attained at a difference of .5 crimes per micro-time hot spot. Importantly, the mean difference of the response and comparison micro-time hot spots was 1.148 (SE = 0.267) crimes. Thus, the unobserved variable would have to produce a significant magnitude of near 1.148 in order to change our conclusions about the impact of the response on crime.

References

Austin, P. C. (2008a). A critical appraisal of propensity-score matching in the medical literature between 1996 and 2003. *Statistics in Medicine*, *27*, 2037–2049.

Austin, P. C. (2008b). The performance of different propensity-score methods for estimating relative risks. *Journal of Clinical Epidemiology*, *61*, 537–545.

Austin, P. C. (2009). Some methods of propensity-score matching had superior performance to others: Results of an empirical investigation and Monte Carlo simulations. *Biometrical Journal*, *51*, 171–184.

Bernasco, W. (2008). Them again? Same-offender involvement in repeat and near repeat burglaries. *European Journal of Criminology*, *5*, 411–431.

Bernasco, W. (2010). A sentimental journey to crime: Effects of residential history on crime location choice. *Criminology*, *48*, 389–416.

Boba, R. (2010). A practice-based evidence approach in Florida. *Police Practice and Research*, *11*, 122–128.

Boba, R., & Santos, R. G. (2011). *A police organizational model for crime reduction: Institutionalizing problem solving, analysis, and accountability*. Washington DC: Office of Community Oriented Policing Services.

Bowers, K. J., & Johnson, S. D. (2005). Domestic burglary repeats and space–time clusters: The dimensions of risk. *European Journal of Criminology*, *2*, 67–92.

Braga, A., Hureau, D., & Papachristos, A. (2012). An ex-post-facto evaluation framework for place-based police interventions. *Evaluation Review*, *35*, 592–626.

Braga, A. A., Papachristos, A. V., & Hureau, D. M. (2014). The effects of hot spots policing on crime: An updated systematic review and meta-analysis. *Justice Quarterly*, *31*, 633–663.

Braga, A. A., & Weisburd, D. L. (2010). *Policing problem places: Crime hot spots and effective prevention*. New York, NY: Oxford University Press.

Coupe, T., & Blake, L. (2006). Daylight and darkness targeting strategies and the risks of being seen at residential burglaries. *Criminology*, *44*, 431–464.

Federal Bureau of Investigation. (2014). *Crime in the United States—2013*. Retrieved December 16, 2014, from http://www.fbi.gov/about-us/cjis/ucr/crime-in-the-u.s/2013/crime-in-the-u.s.-2013

Gangl, M. (2004). *RBOUNDS: Stata module to perform Rosenbaum sensitivity analysis for average treatment effects on the treated.* Retrieved November 11, 2014, http://ideas.repec.org/c/boc/bocode/s438301.html

Gwinn, S., Bruce, D., Cooper, J., & Hick, S. (2008). *Exploring crime analysis: Readings on essential skills* (2nd ed.). Charleston, SC: BookSurge.

Hellerstein, D. (2008). Practice-based evidence rather than evidence-based practice in psychiatry. *Medscape Journal of Medicine*, *10*, 141.

International Association of Chiefs of Police. (2010). *IACP/Sprint Excellence in Law Enforcement Research Award Program: Spotlighting the power & impact of law enforcement academic research partnerships*. Alexandria, VA: Author.

International Association of Crime Analysts. (2011). *Crime pattern definitions for tactical analysis* (White Paper 2011-01). Overland Park, KS: Author.

Johnson, S. D., & Bowers, K. J. (2004). The burglary as a clue to the future: The beginnings of prospective hot-spotting. *European Journal of Criminology*, *1*, 237–255.

Johnson, S. D., Lab, S., & Bowers, K. J. (2008). Stable and fluid hot spots of crime: Differentiation and identification. *Built Environment*, *34*, 32–46.

Johnson, S. D., Summers, L., & Pease, K. (2007). *Vehicle crime: Communicating spatial and temporal patterns*. London, England: Jill Dando Institute of Crime Science.

Johnson, S. D., Summers, L., & Pease, K. (2009). Offenders as forager: A direct test of the boost account of victimization. *Journal of Quantitative Criminology*, *25*, 181–200.

Lum, C., & Koper, C. (2011). The evidence-based policing matrix. *Journal of Experimental Criminology*, *7*, 3–26.

Marginson, F. R., Barkham, M., Evans, C., McGrath, G., Clark, J. M., Audin, K., & Connell, J. (2000). Measurement and psychotherapy: Evidence-based practice and practice-based evidence. *British Journal of Psychiatry*, *177*, 123–130.

Police Executive Research Forum. (2008). *Violent crime in America: What we know about hot spots enforcement. Critical Issues in Policing Series*. Washington DC: Author.

Rosenbaum, P. R. (2002). *Observational studies*. New York, NY: Springer.
Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*, 41–55.
Rosenbaum, P. R., & Rubin, D. B. (1985). Constructing a control group using multivariate match sampling methods that incorporate the propensity score. *The American Statistician*, *39*, 33–38.
Rubin, D. B. (2006). *Matched sampling for causal effects*. New York, NY: Cambridge University Press.
Santos, R. B. (2013a). *Crime analysis with crime mapping*. Thousand Oaks, CA: Sage.
Santos, R. B. (2013b). Implementation of a police organizational model for crime reduction. *Policing: An International Journal of Police Strategies and Management*, *32*, 295–311.
Santos, R. B. (2014). The effectiveness of crime analysis for crime reduction: Cure or diagnosis? *Journal of Contemporary Criminal Justice*, *30*, 147–168.
Santos, R. B., & Taylor, B. (2014). The integration of crime analysis into police patrol work: Results from a national survey of law enforcement. *Policing: An International Journal of Police Strategies and Management*, *37*, 501–520.
Santos, R. G., & Santos, R. B. (2015a). An ex post facto evaluation of tactical police response in residential theft from vehicle micro-time hot spots. *Journal of Quantitative Criminology*. doi:10.1007/s10940-015-9248-7
Santos, R. G., & Santos, R. B. (2015b). Evidence-based policing, "what works" and stratified policing, "how to make it work." *Translational Criminology, Spring*, *8*, 20–22.
Schafer, J. L., & Kang, J. (2008). Average causal effects from nonrandomized studies: A practical guide and simulated example. *Psychological Methods*, *13*, 279–313.
Sherman, L. (1998). *Ideas in American policing: Evidence-based policing*. Washington, DC: Police Foundation.
Sorg, E., Wood, J., Groff, E., & Ratcliffe, J. (2014). Boundary adherence during place-based policing evaluations: A research note. *Journal of Research in Crime and Delinquency*, *51*, 377–393.
Stuart, E. (2008). Developing practical recommendations for the use of propensity scores: Discussion of 'A critical appraisal of propensity score matching in the medical literature between 1996 and 2003' by Peter Austin. *Statistics in Medicine*, *27*, 2062–2065.
Telep, C., Mitchell, R., & Weisburd, D. (2014). How much time should the police spend at crime hot spots? Answers from a police agency directed randomized field trial in Sacramento, California. *Justice Quarterly*, *31*, 905–933.
Telep, C. W., & Weisburd, D. (2012). What is known about the effectiveness police practices in reducing crime and disorder? *Police Quarterly*, *15*, 331–357.

Thoemmes, F. (2012). *Propensity score matching in SPSS*. arXiv preprint arXiv: 1201.6385.

Thoemmes, F., & Kim, E. S. (2011). A systematic review of propensity score methods in the social sciences. *Multivariate Behavioral Research*, *46*, 90–118.

Townsley, M., Homel, R., & Chaseling, J. (2003). Infectious burglaries: A test of the near repeat hypothesis. *British Journal of Criminology*, *43*, 615–633.

Weisburd, D., & Lum, C. (2005). The diffusion of computerized crime mapping in policing: Linking research and practice. *Police Practice and Research*, *6*, 419–434.

Weisburd, D., Telep, C., & Braga, A. (2010). *The importance of place in policing: Empirical evidence and policy recommendations*. Stockholm, Sweden: Swedish National Council for Crime Prevention, Information, and Publications.

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