Longitudinal Study of Crime Hot Spots: 
Dynamics and Impact on Part 1 Violent Crime

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Abstract

Objectives: Design and estimate the impacts of a prevention program for part 1 violent crimes in micro-place crime hot spots.

Methods: A longitudinal study of crime hot spots using 21 years of crime offense report data on part 1 violent crimes from Pittsburgh, Pennsylvania. Based on kernel density smoothing for a definition of micro-place crime hot spots, we replicate past work on the existence of “chronic” hot spots, but then with such hot spots accounted for introduce “temporary” hot spots.

Results: Chronic hot spots are good targets for prevention. They are easily identified and they tend to persist. Temporary hot spots, however, predominantly last only one month. Thus the common practice of identifying hot spots using a short time window of crime data and assuming that the resulting hot spots will persist is ineffective for temporary hot spots. Instead it is necessary to forecast the emergence of temporary hot spots to prevent their crimes. Over time chronic hot spots, while still important, have accounted for less crime while temporary hot spots have grown, accounting for a larger share. Chronic hot spots are relatively easy targets for police whereas temporary hot spots require forecasting methods not commonly in use by police.

Conclusions: The paper estimates approximately a 10 to 20 percent reduction in part 1 violent crimes in Pittsburgh if the hot spot enforcement program proposed in this paper were implemented.

Keywords: crime hot spots, longitudinal study, kernel density smoothing
1. Introduction

Crime hot spots are small areas with high crime densities (Chainey et al., 2008), typically accounting for five percent or less of a city’s area but with on the order of 50 percent of all crimes (e.g., Weisburd et al., 2004; Weisburd et al. 2011). Thus they make good targets for crime prevention, and a number of experimental studies have shown both statistically significant and sizable net crime reductions from additional police resources and innovative tactics allocated to them (e.g., Braga, 2005).

Typically hot spots are identified using cross-sectional data from the most recent period in two-dimensional clustering methods or kernel density smoothing (see Eck et al., 2005). Then, assuming that identified hot spots will persist, police have a number of intervention types for focused or additional police resources including targeted/saturated patrol (Caulkins, 1993), problem-oriented policing (POP) (Clarke and Eck, 2005), and foot patrol (Ratcliffe et al. 2011). Missing from this practice are approaches and methods that deal with the temporal/spatial dynamics of crime hot spots. This paper thus proposes a crime hot spot program for police management of hot spots over time, employing time series methods.

A key paper in the literature on crime hot spots is Weisburd et al. (2004) which extends work on hot spots as micro places and examines their behavior using longitudinal data from Seattle, Washington over a 14-year period. Using trajectory analysis (Nagin, 1999) on annual data for block-long street segments, this paper found that certain hot spots for all crime incidents reported by police officers persist in the long term, and are “chronic.” Clearly some chronic hot spots are extinguished through redevelopment programs, gentrification, and continued police efforts, but these are long-term solutions. From the point of view of police deployment tactics in the short term, such hot spots are chronic also in the sense that they should have a constant presence of additional and innovative police resources.

This paper replicates Wiesburd’s longitudinal study in Pittsburgh, Pennsylvania, but with only part 1 violent crimes, the primary concern of police, and aimed at supporting a crime hot spot program. Furthermore, instead of annual time series data, this study uses monthly data to characterize hot spot dynamics. In addition to chronic hot spots, we introduce “temporary” hot spots. Temporary hot spots are small areas that have the same crime densities as chronic hot spots.
spots (adjusted for short durations) but are not continuous and last for at least a month. The crime hot spot program that we envision thus deploys extra or special police resources constantly to chronic hot spots and as needed to temporary hot spots.

This paper introduces kernel density smoothing (KDS) with a block-long search radius (250 feet in Pittsburgh) as a method for micro-place hot spot estimation. The KDS search radius, a parameter of the method, is radius of the unit-area, bell-shaped surface placed over each crime incident and summed to estimate a smooth crime density surface. Previous crime hot-spot research has used relatively large search radiiuses, such as 820 feet, 1,640 feet, or more (e.g., Chainey 2008). By using a small search radius, however, KDS is limited to only identifying micro places.

KDS’s smoothing is valuable for estimating spatial demand surfaces (demand for police services in this case). It estimates a mean surface, removing spatial randomness. A crime is reported at a given street address or intersection, but may have occurred nearby or over a path involving several locations. For example, the Pittsburgh Police recorded 26 percent of part 1 violent crimes as occurring at intersections, but literally intersections are rarely the actual locations. Instead, the crimes likely occurred on street segments near intersections.

Weisburd et al. (2004) used block-long street segments as micro places, deleting crimes reported as intersections. The Seattle case study in that paper had a lower percentage of crimes reported at street intersections than Pittsburgh, justifying such treatment. For cases such as Pittsburgh, however, it is possible to extend the street-segment approach to micro-place crime hot spots. Drawing on the smoothing idea of KDS, we can allocate 25 percent of intersection crimes to intersecting street segments yielding expected street-segment crime counts overall. This provides a simple but effective alternative to KDS.

To include crimes recorded on both street intersections and along segments, Ratcliffe et al. (2011) used Thiessen polygons centered on all street intersections in Philadelphia, Pennsylvania. Each polygon includes a street intersection and roughly half of each intersecting street segment. A small limitation of this approach, along with that of Weisburd et al. (2004), is that it often identifies only a part of a crime hot spot—the analyst needs to connect contiguous, hot Thiessen polygons or street segments to complete a hot spot. For example, in Pittsburgh we find that
chronic hot spots most often run along several blocks of a commercial corridor. Also in the central business district, the major crime hot spot occupies several blocks in a compact area. KDS automatically provides the boundaries of entire hot spots.

This paper also introduces methods for estimating and analyzing temporary hot spots, including a definition of “on” and “off” for hot spots and use of run-length analysis for frequency of months on and off. An important empirical finding is that temporary hot spots at the monthly time interval predominantly last only one month in summers, the seasonal peak season for serious violent crime. Hence hot spot estimation in practice that uses the most recent data over a few months and assumes that hot spots will persist is ineffective for temporary hot spot enforcement. By the time extra police resources arrive the hot spot is already extinguished. Instead it is necessary to forecast emergence of temporary hot spots (see Cohen et al., 2007, Gorr, 2009, Neill, 2012) in order to prevent or reduce crimes.

Included in this paper’s results is a simple policy simulation that estimates the total impact on part 1 violent crimes in Pittsburgh from a crime hot spot program. Based on this paper’s empirical work and prevention size effect estimated in the literature we find currently that approximately 10 percent of part 1 violent crime is preventable through a hot spot program, half in chronic hot spots and half in temporary hot spots.

Finally, we improve on reporting crime hot spot statistics for a city by removing areas that are not inhabitable such as bodies of water, steep hillsides, and cemeteries. Fifty percent of Pittsburgh’s area is in this category, so when reporting the number of crimes in hot spots and the percentage of inhabitable Pittsburgh (instead of total area) that is in hot spots, we have a more realistic, less optimistic assessment of overall crime densities.

The outline of the balance of this paper follows. Section 2 is a literature review of crime hot spot identification and enforcement, including crime time series forecasting methods. Section 3 describes the 250 month-long data set for Pittsburgh on reported crime incidents. Section 4 discusses our research methods and Section 5 provides results. Finally, Section 6 summarizes the paper.

2. Literature Review
This section reviews the crime theories that explain why crime hot spots methods have become an important approach to policing and how effective they are. It also includes a review of crime forecasting methods.

2.1 Crime place theories

Historically, scholars were more focused on criminal individuals rather than crime places, explaining the occurrence of crime by human factors, such as psychology and criminal motivation (Eck and Weisburd, 1995). From the early 1990s, however, a number of studies had begun emphasizing the criminology of place in the context of relatively new crime theories. Cohen and Felson (1979) introduced routine activity theory which emphasizes recognizable crime targets and lack of capable guardianship as significant factors in the occurrence of crimes. If a motivated offender is present with a desirable target, no guardian on this target elevates the risk of victimization. Eck and Weisburd (1995) advanced rational choice theory to explain why criminals select particular places as their targets and impose special means to achieve their goals. Together, routine activity and rational choice theories became components of crime pattern theory (Eck and Weisburd, 1995) to explain the distribution of crimes in places. Crime pattern theory concerns the interactions of offenders with targets, handlers, guardians, and managers, as well as socio-physical environments.

As documented in the next section, relatively few places in an urban environment are highly conducive to crime, so crime tends to be highly concentrated in small areas—hot spots. Crime place theories explain why these places are conducive to crime. Electronic record management systems introduced in the late 1980s in major police departments and the emergence of geographic information system (GIS) at the same time for displaying and analyzing crime locations made hot spot enforcement feasible. It was expected that total the number of crimes could be reduced if suitable police interventions were used in hot spots (Sherman and Weisburd, 1995; Weisburd and Green, 1995).

2.2 Empirical evidence on hot spot crime densities

Crime hot spots are attractive targets for police because a large percentage of urban crime is concentrated in small areas (Brantingham and Brantingham, 1982). For example, Sherman et al.
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(1989) found that only about three percent of addresses and intersections accounted for 50 percent of all dispatched police calls for service in Minneapolis. Weisburd and Green (1995) reported that roughly four percent of the street sections and intersections in Jersey city, New Jersey accounted for 86 percent of narcotics sales arrest, and about 84 percent of all emergency calls for service. Weisburd et al. (2004) found that about five percent of street segments accounted for 50 percent of all crime incidents in Seattle over a 14-year period. Ratcliffe et al. (2011) found in Philadelphia that the top one percent of street corners accounted for 15 percent of robberies, 13 percent of aggravated assaults, and over 10 percent of all homicides in summer 2008. Weisburd et al. (2011) found that hot spots for juvenile crimes occupied less than one percent of street segments but accounted for 50 percent of juvenile crime events, while nearly all juvenile crimes were concentrated in only five percent of street segments in Seattle.

2.3 Empirical evidence on hot spot persistence

Operationally, police identify hot spots from historical data and then allocate resources to reduce crimes in them, assuming that the hot spots will persist. Chainey et al. (2008) is one of the few researchers who studied short-term persistence of hot spots. He estimated street-crime hot spots as the top three percent crime density areas from kernel density smoothing with three month’s data and then determined if the hot spots persisted an additional month. The results varied by crime types: only 20 percent of the street crimes, 12 percent of theft from vehicle, 10 percent of theft of vehicle, and 8 percent of burglary persisted in the hot spots. Apparently the hot spots were predominantly temporary in duration.

In contrast, if some hot spots persist for long periods of time, police should allocate additional resources constantly to them. There is a small literature using longitudinal data to study the long-term persistence of hot spots. Some evidence on the long-term persistence of high density crime areas goes back to early twentieth century in Chicago. Shaw and Mckay (1942) presented the overall patterns of delinquency rate in Chicago using 20 year’s data. In spite of the fluctuation of population, inadequate housing, poverty, multiple races, foreign-born, and other socio-environmental factors, delinquency rates in high density crime areas remained stable. Schmid (1960) observed the frequency change of homicide, rape, robbery, and burglary in two different periods, one from 1939 through 1941, another from 1949 through 1951 in Seattle.
Community zones that were in high density areas of selected violent crimes remained high, while zones in low crime density still remained low. Another longitudinal study, Schmid (1960), in Minneapolis also supported the persistent nature of high density crime areas: those in 1933 still remained high in 1936.

More recently, Spelman (1995) used cross-sectional pooled time series data to study the variability of crime by 28-day periods within three year’s crime data from Boston. Similar to other hot spots, only 10 percent of the worst places and times accounted for 50 percent of all calls for service and a high degree of persistency was observed. Another longitudinal study in Baltimore, Maryland, Taylor (1999), showed that crime, “grime,” and fear on 90 street blocks and respondents from the interviewed residents did not change significantly between 1981 and 1994. Current research on long-term persistence of crime hot spots was conducted by Weisburd et al. (2004), which found that only five percent of street segments account for 50 percent of all crime incidents in Seattle over a 14-year period. In addition many hot spots persisted for the entire 14 years of the study.

2.4 Crime displacement

Despite the attractiveness of hot spots for police enforcement, a number of studies have challenged that hot spot enforcement on particular types of crimes or specific locations may lead crime to displace to non-targeted areas so that at worst there is no net reduction in crime (Reppetto, 1976). However, Hesseling (1995) asserts that displacement is not complete and not always inevitable, even though most enforcement tactics may result in displacement.

Weisburd (2006) found that crime displacement is not significant in drug and prostitution crime hot spots. He found that such market-based crimes do not simply displace to other places, because of the offender’s natural tendency to stay in familiar circumstances. Ratcliffe et al. (2011) estimated displacement using the Bowers and Johnson (2003) approach. This study found that of a total reduction of 90 violent crimes in the Philadelphia foot patrol experiment, 37 were displaced leaving a net reduction of 53 crimes.

A contrary line of research suggests that hot spot displacement, if it exists, could result in a desirable consequence from the effective police enforcement—diffusion of benefits. If the
potential threat of police enforcement grows, the volume of crime would reduce greater in area than anticipated. This completely opposite effect to displacement was coined as “diffusion of benefits” by Clarke and Weisburd (1994), “halo” effect by Scherdin (1992), and “free rider” effect by Miethe (1991). Caulkins (1993) pointed out that police interventions on hot spots can be worthwhile efforts to the reduction of total number of crimes, because sub-optimal locations will benefit from the policing. Weisburd (2006) found that there was a statistically significant decrease in the number of observed prostitution and drug activities not only in target areas, but also in larger catchment areas. Braga (1999) found that the overall reduction of violent crime indicators by problem oriented policing (POP) was dominant in treatment areas compared to control areas, while displacement effect and diffusion of benefits were not significant. The above discussion suggests that the phenomenon of hot spot displacement and diffusion of benefits is highly complex (Hesseling, 1994). Further studies will be needed to measure and evaluate the net effect of police enforcement on hot spot places to maximize the utility of police resources.

2.5 Evidence on hot spot enforcement size effects

A number of studies have demonstrated that police interventions in crime hot spots reduce crime. Weisburd and Green (1995) employed a randomized experiment to evaluate the effectiveness of the National Institute of Justice’s Drug Market Analysis Program (DMAP) in Jersey City, New Jersey. The number of emergency calls for service was reduced significantly in 28 experimental hot spots which received innovative enforcement strategies compared to 28 control hot spots which had traditional drug enforcement strategies. Even though an increase in calls for service was expected due to the activity increase in summer seasons, the overall number of disorder calls for service increased only 256 in experimental hot spots, while the increase in control hot spots was 700 calls for service. This yielded a 63 percent reduction in the expected number of crimes.

Another experiment in Minneapolis, Minnesota (Sherman and Weisburd, 1995) provided evidence on the effects of hot spot enforcement. Among 110 hot spots from 420 address crime clusters, 55 hot spots were assigned to a treatment group in which officers increased patrol presence by three hours per day compare to 55 control hot spots that did not get the increased patrol. The additional patrols led to modest, but statistically significant deterrent effects ranging from 6 to 13 percent reduction in total number of calls for service.
Braga (2005) is a meta study of five randomized experiments estimating overall effect size of police enforcement in experimental areas: Jersey City problem-oriented policing strategy (POP) at violent places (Braga et al., 1999), Kansas City crack house raids (Sherman and Rogan, 1995), Minneapolis hot spots patrol experiment (Sherman and Weisburd, 1995), Jersey City Drug Market Analysis program (DMAP) experiment (Weisburd and Green, 1995), and Minneapolis Repeat Call Address Policing (RECAP) experiment (Sherman et al., 1989). In the Jersey City POP, Kansas City Crack House Raids, and Minneapolis Hot Spots Patrol experiment, the total number of calls for service was used to estimate the effect size of each experiment, while Jersey City DMAP experiment used only disorder calls for service. The Minneapolis RECAP experiment also used total calls for service to measure the effect size, but effect sizes were estimated for residential and commercial areas, respectively.

Each study’s results were weighted by the inverse of variance to estimate the reduction effect size in number of calls for service in target areas. The overall mean size effect due to hot spot intervention was 0.345. The Minneapolis RECAP experiment had a very small non-significant effect size in both residential and commercial areas. As the small non-significant effect sizes were counted higher than those of other studies due to relatively small standard error, overall effect size increased to 0.632 by dropping RECAP experiment from the meta analysis, which is classified as moderate effect size by Cohen's conventional criteria (Cohen, 1988).

Braga et al. (1999) used a fixed-effects method to measure POP impact on 12 paired violent crime hot spots (one member of each pair was under treatment, otherwise, controlled) in Jersey City, New Jersey. Two types of crime data were collected, Calls for service (CFS) and crime incident data. The main effect of POP on aggregated crime counts and six types of citizen calls for service of 12 treatment hot spots were 38 percent and 15 percent reduction in total number of counts of each crime data, respectively. For the POP impact on individual types of CFS and crime incidents, street fights CFS had 60 percent reduction, narcotics CFS a 28 percent reduction, and robberies a 63 percent reduction, all statistically significant without crime displacement.

Taylor et al. (2011) studied the deterrent effect of different enforcement strategies. Eighty-three hot spots of serious violent crime were randomly assigned to a control group of 40, 21 to a saturation/directed patrol group, and 22 to POP hot spots. The only significant effect was POP on
Ratcliffe et al. (2011) examined foot patrol effects on violent crime hot spots in Philadelphia. This study identified 120 foot patrol areas by including at least one of the top 220 Thiessen polygon hot spots centered on street intersections. Employing a randomized block design to evaluate the foot patrol effect, 53 violent crimes (i.e., 23 percent) net reduction effect was calculated considering hot spots displacement. Target areas in the top 40 percentile on pre-intervention violent crime counts had significant reduction effect during the three month operation phase.

The overall range of reported size effects is 6 to 63 percent with a median of 33 percent, the value we use in a policy simulation below.

2.6 Crime Forecasting

Cohen et al. (2004) and Gorr (2009) developed a leading indicator model to forecast serious property and violent crimes in crime places based on broken windows theory (Kelling and Coles, 1997) and that criminals are generalists (e.g., Gottfredson and Hirschi, 1990). They showed that certain lesser crimes and computer-aided dispatch calls for service—for example, simple assaults, drug calls for service, and shots fired calls for service—lead serious violent crimes. Thus if in the past month or few months there is an increase in leading-indicator crimes then it is likely that serious violent crimes will increase in the next month.

Using the top few percentage points of the serious violent crime distribution as the definition of actual hot spot increases or positives, Gorr (2009) found that true positive rates varied from 25 to 33 percent at false positive rates acceptable to police (between 15 to 20 percent). These results are based on monthly time series data for census tracts. Recent work on the crime leading indicator model by Neill (2012) using a spatial scan statistic (Neill, 2009) at the city block level and with weekly data finds a true positive rate of 60 percent with a false positive rate of 15 percent for serious violent crimes. We use the latter results in the policy simulation later in this paper.

3. Data
Pittsburgh, Pennsylvania, our study area, is a city of approximately 306,000 population and 55 square miles. It has six police zones and 42 car beats. The crime data for this research are individual incidents of part 1 violent crimes (homicide, rape, robbery, and aggravated assault) over nearly 21 years from January 1990 through October 2010. These data provided by Pittsburgh Bureau of Police were appended from two records management systems, one that functioned from 1990 through 1999 and the other from 2000 to date. The volume of aggravated assaults nearly tripled in the period from 2000 through 2002. Interviews with Pittsburgh Police crime analysts did not identify a clear cause for this increase, but it appears to be due to changes in coding and reporting practices. Robberies peaked in the early 1990s during the crack epidemic while rape generally declined and homicide had a slight increasing trend. Table 1 provides corresponding statistics on the data. This study excludes certain part 1 violent crimes from analysis (e.g., assaults against police officers, theft from buildings, and retail theft) that are not part of the public’s threat of being victims of street-level offenses.

**Table 1. Annual part 1 violent crime statistics in Pittsburgh: 1990 through 2010**

<table>
<thead>
<tr>
<th>Year</th>
<th>Murder-Manslaughter</th>
<th>Forcible Rape</th>
<th>Robbery</th>
<th>Aggravated Assault</th>
<th>Part 1 Violent Crime Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>Min</td>
<td>14</td>
<td>58</td>
<td>1,003</td>
<td>511</td>
<td>1,988</td>
</tr>
<tr>
<td>Max</td>
<td>68</td>
<td>278</td>
<td>2,566</td>
<td>1,529</td>
<td>3,538</td>
</tr>
<tr>
<td>Mean</td>
<td>37</td>
<td>181</td>
<td>1,636</td>
<td>997</td>
<td>2,850</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>13</td>
<td>56</td>
<td>379</td>
<td>367</td>
<td>483</td>
</tr>
</tbody>
</table>

The crime incident locations were geocoded using an ArcGIS 10 locator for US Streets with default settings, but no side offset, and a 2010 TIGER map for street centerlines downloaded from the U.S. Census Bureau’s website. For mapping and analysis, the crime locations were projected to a state plane coordinate system (feet). As seen in Table 2, overall 84 percent of part 1 violent crime was matched, which is close to Ratcliffe’s (2004) acceptable rate of 85 percent.
Factors that may be associated with violent crime hot spots are poverty and commercial land use. Three different variables from the 2000 census at the block group level were used as indices for the poverty in Pittsburgh: population with less than high school education, males in the workforce who are unemployed, and population below poverty income. These three indices were combined into a poverty index averaging standardized values of the three variables (Dawes, 1979). Finally, contour polygons from the top 3.7 percent, or z-score higher than 1.795 of the surface obtained by kernel density smoothing define poverty areas in this paper. The threshold poverty index value was selected judgmentally but the resultant areas correspond to well-known poverty areas of Pittsburgh. Commercial zones are also presumed to correlate with hot spots locations, thus the paper uses polygons for commercial zoning obtained from the Pittsburgh City Planning Department. The commercial areas used in this paper are dissolved polygons for all types of commercial zoning.

4. Research Design

This section describes how we processed the 21 years of part 1 violent crime data of Pittsburgh, Pennsylvania to create chronic as well as temporary hot spots. Hot spots are generated using the kernel density smoothing (KDS) method for crime density surface estimation. We use a relatively small cell size—fifteen feet on a side—to generate smooth KDS contour lines. We use a block-long search radius (250 feet) to identify micro-area hot spots comparable to the block-long street segments defining hot spots in Weisburd et al. (2004) and street-intersection-based Thiessen polygons in Ratcliffe et al. (2011). Chronic hot spots, similar to those in Weisburd et al (2004), use cross-sectional data from all 21-year’s part 1 violent crime data, while temporary hot spots use KDS maps estimated from monthly time series of as explained below.
Over the long run of a decade or more, one can imagine that changes in police methods, urban redevelopment, and other factors could influence chronic crime patterns. Nevertheless, all that is needed for police resource allocation is a determination of currently-chronic crime hot spots such as provided by a multiple-year moving window of data. For the purpose of designing a crime hot spot program, this paper uses a three-year moving window of data to estimate chronic hot spots.

### 4.1 Chronic hot spots

Two criteria define chronic hot spots. First, somewhat arbitrarily, we use the top one third standard deviation breakpoint of the KDS map as the threshold to determine candidates for chronic hot spots, resulting in the top 0.23 percent, or z-score higher than 2.833 of the KDS score. Such a threshold necessarily is judgmental and in practice needs to be determined by police policy makers. Second, chronic hot spots must have at least 250 part 1 violent crimes (an average of one per month over the total data sample). This second criterion eliminates many very small areas as chronic hot spots. Pittsburgh has 14 chronic hot spots that existed throughout the 1990s and 2000s.

Chronic hot spots are not “on” 100 percent of the time on a monthly basis; some months they are “off.” We define hot spots as “off” for a given month when the monthly density of a given hot spot is lower than the average density of the non-chronic hot spot areas of inhabitable Pittsburgh at the monthly level. Otherwise, hot spots are “on.” Uninhabitable areas include cemeteries, greenways, landfills, landslide areas, parks, water bodies, rivers, and woodland. Finally, we studied dynamic behavior of chronic hot spots by tabulating run lengths of individual chronic hot spot which accounts for the duration and frequency of months “on” among chronic hot spots.

### 4.2 Temporary hot spots

Using the same “on” and “off” densities as chronic hot spots (but adjusted to month-long time periods), KDS areas which include at least two part 1 violent crimes per month and are not single point locations are classified as temporary hot spots. We use these criteria on KDS estimates.
made with chronic hot spot crime points removed from the data.

4.3 Study periods

The analysis in this paper focuses on the peak season for part 1 violent crime in “before” and “after” periods relative to long-term changes in policing and the Pittsburgh urban landscape. Summers are peak months for part 1 violent crime in Pittsburgh and elsewhere (Gorr et al., 2003), hence this paper analyzes chronic and temporary hot spots for the summer months of June, July, and August. We analyze summers over two time periods: 1993–1995 and 2007–2009 to provide samples representing “before” and “after” periods. During 1993–1995 the Pittsburgh Bureau of Police had no computerized crime mapping and Pittsburgh had several high-crime areas including multiple public housing projects and blighted neighborhoods. By 2007–2009, the Pittsburgh Police had an experienced crime analysis unit in place using computerized crime mapping, a CompStat management system including crime map reporting, and availability of crime mapping to police officers city-wide. Most of Pittsburgh’s public housing had been torn down with former residents scattered throughout the city and major urban redevelopment projects were having an effect on formerly blighted neighborhoods, including the central business district’s theater district and the Lawrenceville, East Liberty, and Lower Hill District neighborhoods. We expected chronic hot spots to be diminished in the “after” period as compared to the “before” period.

5. Results

Figure 1 presents the KDS map generated for part 1 violent crime in Pittsburgh, Pennsylvania using all crime points for the period January 1990 through October 2010. Evident is the highly-clustered nature of these crimes. The triangular cluster near the center of Pittsburgh is in the central business district.

Figure 2 displays the 14 chronic hot spots resulting from the criteria described in the previous section, while Figure 3 is a blow-up of the central business district’s chronic hot spots with 500 foot buffers added. We suggest that police allocate additional resources to buffer extensions of chronic hot spots because a significant percentage of temporary hot spots occurs in them (about 25 percent as seen below) and the marginal costs of their enforcement would be low.
Table 3 provides a breakdown by individual part 1 violent crimes of the percentage of crime in hot spots for the full data set. Robbery has the highest concentration, 21 percent, while forcible rape was the lowest (as might be expected), but still relatively high at 12 percent. In Table 3 we see that 17.1 percent of part 1 violent crimes were concentrated in chronic hot spots which account for only 1.5 percent of inhabitable areas in Pittsburgh. Also crime density in chronic hot spots is 732 per million square feet while it is only 52 per million square feet in inhabitable areas of entire Pittsburgh excluding chronic hot spots areas. Chronic hot spots have 14 times the crime density than other inhabitable areas.

![Map of kernel-density-smoothed part 1 violent crimes in Pittsburgh: 1990 through 2010 with 250 foot search radius](image)

**Fig 1.** Map of kernel-density-smoothed part 1 violent crimes in Pittsburgh: 1990 through 2010 with 250 foot search radius
Fig 2. Map of part 1 violent crime chronic hot spots in Pittsburgh: 1990 through 2010

Fig 3. Close-up map of part 1 violent crime chronic hot spots with 500 foot buffers in Pittsburgh: 1990 through 2010
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While chronic hot spots may persist in the long-term, they can turn on and off on a monthly basis. Figure 4 shows the frequency distribution for chronic hot spots being “on.” The figure shows that five of the 14 chronic hot spots are on between 90 and 100 percent of the 250 months of the data sample (one was on 100 percent of the time). Some of the hot spots with lower frequency of “on” months were eliminated in the latter part of the 21-year period, partly accounting for lower frequency of on months.

Table 3. Percentage of total of part 1 violent crimes in chronic hot spots

<table>
<thead>
<tr>
<th>UCR</th>
<th>Description</th>
<th>Hot Spot Crimes</th>
<th>Pittsburgh Crimes</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Murder-manslaughter</td>
<td>88</td>
<td>682</td>
<td>12.9%</td>
</tr>
<tr>
<td>2</td>
<td>Forcible rape</td>
<td>336</td>
<td>2,896</td>
<td>11.6%</td>
</tr>
<tr>
<td>3</td>
<td>Robbery</td>
<td>5,925</td>
<td>28,879</td>
<td>20.5%</td>
</tr>
<tr>
<td>4</td>
<td>Aggravated assault</td>
<td>2,265</td>
<td>17,909</td>
<td>12.6%</td>
</tr>
<tr>
<td></td>
<td>Total part 1 violent crime</td>
<td>8,614</td>
<td>50,366</td>
<td>17.1%</td>
</tr>
</tbody>
</table>
Using data from the before and after periods of this study, Figure 5 shows that temporary hot spots mostly last only a month. We see that 131 out of 140 temporary hot spots that started in the stated month for 1993 through 1995 persisted only one month. For the same period from 2007 through 2009, the total number of temporary hot spots had increased and 195 out of 205 temporary hot spots persisted one month.

In practice, police would not use 21 years of data to define chronic hot spots because long-term forces can change chronic hot spots. Hence Table 4 provides results for chronic hot spots based on three years of data for the before periods 1993–1995 and after periods 2007–2009. For example, 1993 chronic hot spots use data from 1990–1992 for their definition, and 2009 uses 2006–2008 data.
Table 4 shows that 32.1 percent of total part 1 violent crime in the summer months of 1993 were in chronic hot spots but in 2007 this figure reduced to 16.6 percent were in chronic hot spots, which became 12.7 percent in 2009. The main driver for the overall 50 percent reduction of part 1 violent crime was decrease in forcible rape and robbery in chronic hot spots.

Fig 5. Distribution of on and off run lengths for 1993 through 1995 and 2007 through 2009 temporary hot spots started at June, July, and August in Pittsburgh

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Table 4. Statistics for chronic hot spots in Pittsburgh: before and after years

<table>
<thead>
<tr>
<th>Year</th>
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<th>Total</th>
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<tbody>
<tr>
<td>1993</td>
<td>13</td>
<td>35</td>
<td>632</td>
<td>186</td>
<td>866</td>
<td>32.1%</td>
</tr>
<tr>
<td>1994</td>
<td>5</td>
<td>37</td>
<td>521</td>
<td>168</td>
<td>731</td>
<td>31.1%</td>
</tr>
<tr>
<td>1995</td>
<td>5</td>
<td>45</td>
<td>360</td>
<td>127</td>
<td>537</td>
<td>26.6%</td>
</tr>
<tr>
<td>2007</td>
<td>8</td>
<td>5</td>
<td>286</td>
<td>161</td>
<td>460</td>
<td>16.6%</td>
</tr>
<tr>
<td>2008</td>
<td>14</td>
<td>3</td>
<td>218</td>
<td>127</td>
<td>362</td>
<td>13.2%</td>
</tr>
<tr>
<td>2009</td>
<td>8</td>
<td>5</td>
<td>286</td>
<td>161</td>
<td>460</td>
<td>12.7%</td>
</tr>
</tbody>
</table>

Table 5 provides the monthly average part 1 violent crimes in both chronic and temporary hot spots for before and after periods. Even though the total number of part 1 violent crimes increased in 2000s, the percentage of part 1 violent crime in chronic hot spots decreased about 50 percent (as seen in Table 4) while it increased about 20 percent in temporary hot spots. A two tailed t-test of differences in part 1 violent crime in chronic hot spots between 1990s and 2000s is highly significant (p-value < 0.0001) and significant at the 0.10 level for temporary hot spots (p-value = 0.076).

Table 5. Monthly average part 1 violent crime in hot spots for before and after periods

<table>
<thead>
<tr>
<th>Period</th>
<th>Temporary Hot Spots Average Monthly P1V</th>
<th>Chronic Hot Spots Average Monthly P1V</th>
<th>Non Hot Spot Average Monthly P1V</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Before”</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>“After”</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2007–2009</td>
<td>56</td>
<td>35</td>
<td>152</td>
<td>243</td>
</tr>
</tbody>
</table>

Figure 6 displays all temporary hot spots for the 18 months of the before and after study periods. While temporary hot spots collectively appeared at a great many locations, many were proximate to chronic hot spots. Using 500 foot buffers around chronic hot spots (see Figure 3), about 25 percent of temporary hot spots are included in the buffers.
Figure 7 is a map showing the relationship of violent crime hot spots to a poverty index and commercial land use for the case of July 2009. All chronic hot spots are within or intersect poverty lines, while most temporary hot spots overlap with or are contiguous to commercial zones in July 2009.

Finally, Figures 8 and 9 roughly estimate the summer-time crime reduction by police enforcement in chronic and temporary hot spots based on results in Table 5. Also, we use the median effect size of 33 percent for enforcement determined in the literature and the true positive rate of 60 percent for forecasting from Neill (2012). The total estimated reduction in part 1 violent crime is 14.6 percent for the before period but drops to 10.3 percent for the after period, due to the decrease in chronic hot spot crimes. While under before conditions two thirds of the total reduction was due to chronic hot spot enforcement, it drops to half under after conditions. Instead of using the median size effect for enforcement of 33 percent in the literature, if we were to use the maximum effect of about 60 percent, the total reductions would double in both the before and after periods.
Fig 7. Map of crime hot spots, commercial, and poverty areas in Pittsburgh for July 2009
Fig 8. Probability tree estimating the size effect of a police hot spot program in Pittsburgh for summers (1993 through 1995)

Fig 9. Probability tree estimating the size effect of a police hot spot program in Pittsburgh for summers (2007 through 2009)
6. Conclusion

This paper proposed a crime hot spot enforcement program for part 1 violent crimes that allocates additional police resources to chronic hot spots on a continuing basis and to forecasted temporary hot spots on an as-needed basis. The paper introduced kernel density smoothing (KDS) as an estimation method for micro-place crime hot spots, using a block-long search radius (250 feet in Pittsburgh) and a high crime density threshold. For implementation, we propose using a multiple-year, moving window of data (three years in this paper) to identify chronic hot spots. Using the same crime density threshold, plus a criterion of at least two part 1 violent crimes at different locations per month, the same methodology applied to a month’s data defines temporary hot spots.

A hot spot, whether chronic or temporary, is defined to be off for a month when its crime density is at or below the crime density of inhabitable areas of Pittsburgh that are not chronic hot spots. Predominantly, temporary hot spots for part 1 violent crime only persist for a month, so early detection is less likely to be effective than forecasting for enforcement. Hence the common police practice of estimating crime hot spots using a short data window of recent data (a simple approach for detection) is not effective for part 1 violent crime—normal policing or other forces eliminate temporary hot spots by the time additional police resources are in place.

Overall the paper estimated roughly a 10 percent reduction in part 1 violent crimes due to crime hot spot enforcement with half from chronic hot spots and half from temporary hot spots (based on summer results for 2007 through 2009). Note that besides the costs due to enforcement and losses by victims, that the emergence and persistence of crime hot spots has additional societal costs including fear by the public, loss of confidence in police, and loss of economic vitality of commercial areas. So a cost/benefit analysis of the impact of crime reduction in hot spots likely would place higher value on crime reductions in hot spots than elsewhere.

Our recommendation to police at this stage of research for enforcement of part 1 violent crime during summer peak periods is to develop a crime hot spot program with the following elements.

Chronic crime hot spots: Use a period of crime incident data of three or more years ending
recently to define chronic hot spots. Apply KDS to this data using the average block length of the jurisdiction for search radius with a high threshold crime density (corresponding to the top one percent or less). Design an enforcement and prevention program for chronic hot spots using the best evidence-based approaches available in the literature and apply them continually.

Temporary crime hot spots: Stop any efforts at identifying crime hot spots using a short interval of recent data, of one to several months, assuming that such hot spots will persist. They will not persist. Instead, forecast the emergence of temporary hot spots using a leading-indicator, crime forecast model such as Neill’s CrimeScan as used by the Chicago Police Department.

Chronic crime hot spots buffers: Extend enforcement areas around chronic hot spots to include buffer areas. For example, 500 foot buffers cover about 25 percent of temporary hot spots. With additional police resources already deployed in chronic hot spots, there likely is low marginal cost to extend efforts into surrounding buffer areas while gaining a significant increment of benefit.

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