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The Deterrence Effect Revisited: Spatial Analysis of the Impact of Police Presence on the Probability of Crime

Toger Marina, Benenson Itzhak, Weisburd Sarit

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The Deterrence Effect Revisited: Spatial Analysis of the Impact of Police Presence on the Probability of Crime.

Toger Marina [a,b], Benenson Itzhak [a], Weisburd Sarit [a][1]

[a] Tel Aviv University, [b] Uppsala University

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Abstract

Smart data-driven policing aims to achieve maximum visibility, short response times, and minimal crime with limited resources. At the heart of data driven policing, there is a need to understand how the spatiotemporal patterns of police presence impact the occurrence and distribution of crime. The causal impact of police presence on crime remains a mystery with some researchers finding that relocating police forces did not significantly impact crime occurrence, while others report that concentrated police presence decreases the probability of crime in the area.

Recently available high-resolution spatial data on police presence and emergency calls to police enable revisiting this question with big-data analysis techniques. In this project, we analyse detailed AVL records of police locations alongside crime locations, time-stamped from 911 call records in Dallas, Texas USA during 2009. We develop a statistical model of spatiotemporal dependence between police vehicles and emergency calls and document the correlation between the location of law enforcement and the probability of reported misconduct. The critical issue of significance of the revealed dependency is studied with the help of statistical simulation, based on randomised datasets: mapping out the relationship void of any interaction effect between police and crime and contrast these simulations to what is actually observed in the data

We find that the proximity of police officers to a given location is more likely to be positively correlated with an increase in future crime than a decrease, even when controlling for geographic fixed effects. We suggest possible mechanisms for this relationship and discuss the implications for optimising preventative patrol with the goal of reducing crime.

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1. Introduction

With growing urbanisation as well as upsurge in human population, increasing attention is being paid to smart policing, where limited resources are deployed in an optimised fashion to achieve maximum visibility, shortest response times and, finally, to minimise crime. At the heart of smart policing, there is a need to analyse the relationship between spatiotemporal patterns of police presence and the occurrences of crime.

This paper is about the possible immediate deterrence effect created by police presence. We examine this relationship using a dataset of disaggregated 911 calls, crimes, and precise police vehicle location records in Dallas, Texas USA and focus on place-based deterrence and spatiotemporal heterogeneity of crime and policing.

By deterrence here we mean the preventive effect of actual or threatened punishment upon potential offenders as a reaction to police presence in locations of potential crime, as in Ball (1955). Deterrence depends on sanction risk perception (Durlauf S. N., 2010): celerity, certainty and severity of punishment (Beccaria, 1764; Bentham, 1970). Police presence affects risk perception and thus is expected to have a deterrence effect. The literature provides mixed evidence of the deterrence effect of police presence. Some studies found no significant (Hunt et al., 2014; Kelling et al., 1974; Nagin et al., 2015; Weisburd, D. & Eck, J., 2004) deterrence effects while others point to limited effects (Nagin et al., 2015; Paternoster, 2010) or strong (Weisburd, S., 2021) deterrence. Weisburd (2021), found that a 10% decrease in police presence in a geographically defined beat (~5000 residents) in Dallas USA resulted in a 7% increase in crime.

All the above studies are based on spatially aggregated data - by beat or other reporting area. The analysis of aggregated crime data was recently criticized by Wheeler & Reuter (2020) who reinstate the Modifiable Areal Unit Problem (MAUP, Openshaw, 1981) and inevitable bias caused by spatiotemporal aggregation of the heterogeneous data. The phenomenon of crime is highly heterogeneous both in space and in time and in this paper, we re-examine the deterrence effect of police presence based on the unique spatially explicit dataset of crime location and police presence at resolution of a single crime event and police vehicle location.

According to the Routine Activity Theory, the possibility of the crime event depends on three drivers - opportune location, available target victims, and motivated offenders (Cohen & Felson, 1979). Each of these three elements are controlled by place manager (e.g., lighting), offender handler (e.g., parents), and target guardian (e.g., security guard, police). A crime becomes more probable if the controllers are missing or not functioning. Drivers and controllers are distributed across space very unevenly thus requiring both place based *and* person focused policing (Weisburd et al., 2012). Uneven spatial distribution of locational opportunities of crime is relatively steady, leading to crime hotspots that remain stable over time (Weisburd et al., 2012). Weisburd's (2015) law of crime concentration that was tested across multiple cities, states that between 2.1 to 6 percent of the city areas stably includes 50% of the crime, while slow population processes, like gentrification, can lead to the slow hotspots dynamics, at least of some crime types (Malleson & Andresen, 2016). The offenders introduce additional spatial heterogeneity via their individual awareness space that is heterogeneous across space and time (Brantingham & Brantingham, 1999).

In what follows, we focus on location- and time- deterrence, namely on time-place-based policing and consider short-term deterrence. Previous research has shown that large increases in police presence, specifically at hotspots, reduce crime there (Sherman, L. W. et al., 1998; Weisburd, D. & Eck, J., 2004), and we test whether this relationship can be observed when looking at naturally occurring changes in police location and high-resolution data.

In the following section 2, Methods, we describe the research area, the data and data processing procedures. In the section 3 we describe the results, following by the concluding section 4.

2. Methods

2.1 Study area and data sources

Dallas, TX, was ranked the 9th city in USA in terms of population size, numbering 1.2 million people in the 2010 census (United States Census Bureau, Population Division., 2020). Dallas crime and policing has been examined in several studies (see for instance (Wheeler & Reuter, 2020) and citations within), with some of the data publicly available on the Dallas OpenData portal (Dallas, City Hall, 2021) available in a new platform from 2015 (Tyler Technologies, 2018) and containing data from 2003 and onwards. Our research team was fortunate to obtain access to an even more detailed database of 911 call records (N=684,584), and crime records (N=215,230) for the year 2009. Importantly, we were also able to gain access to the police Automated Vehicle Locater (AVL) records (72M records, see

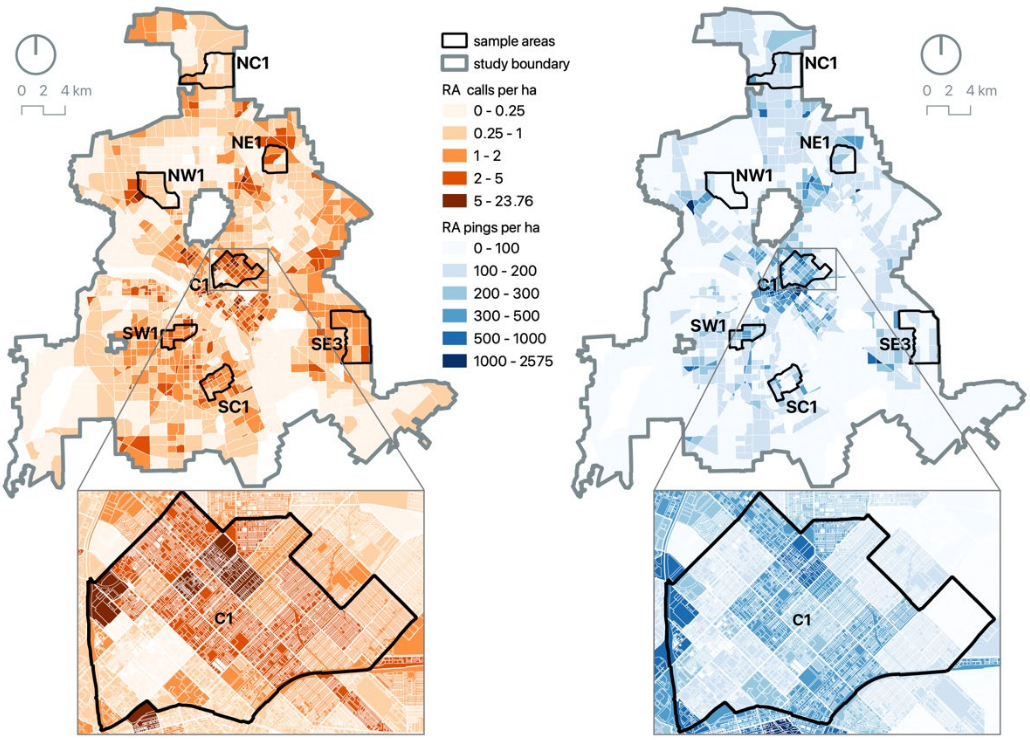

Figure 1). The 911 calls were selected as a proxy for actual crime activity as opposed to crime records that contain only those incidents that are summarized in a crime report.

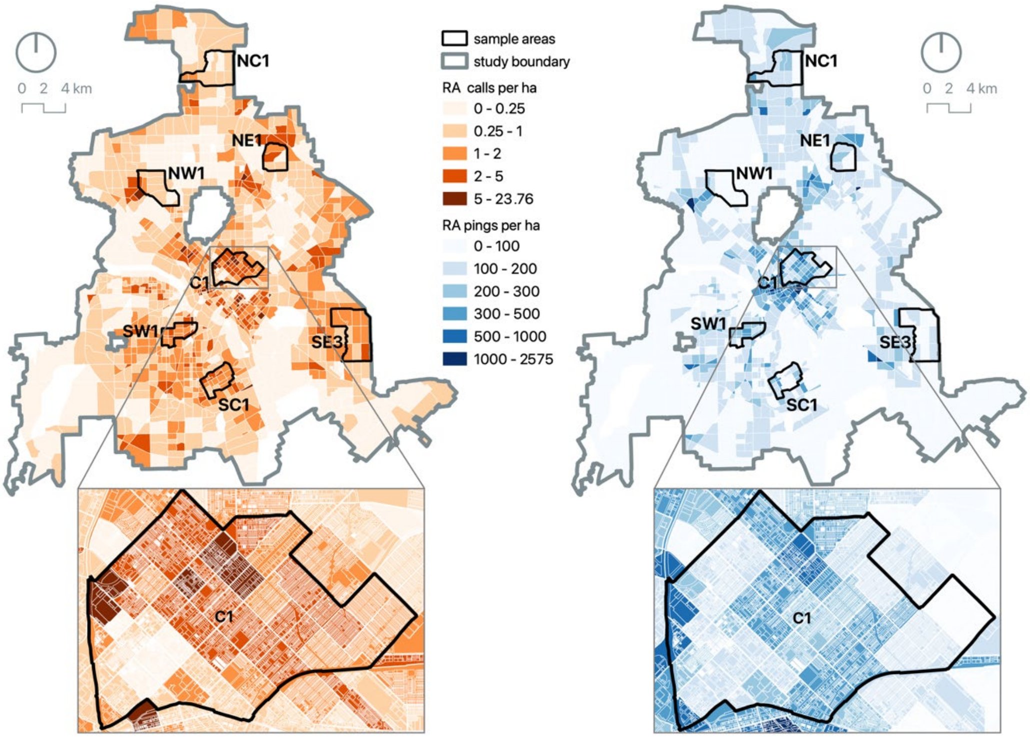

Figure 1: Distribution of 911 calls in Dallas, TX, per ha by reporting area (left) and police presence (GPS pings) per ha by reporting area (right), with this study's sample areas denoted in a black line. Both police and 911 calls were taken for the study time period June-September 2009 17:00-23:59:59. Close up of the central sample area C1 is shown below with the parcels (lots, our main analysis unit) delineated in thin white lines and reporting areas (RA) in thick white lines.

All datasets mentioned above contain the exact location and time of each event and police vehicle ping. The 911 calls in the database contain latitude and longitude of the call location. We represent locations of calls at the resolution of residential lots (called "lots" further) as the location of the crime. The layer of the lots is available at the City of Dallas web data portal, http://gis.dallascityhall.com/Downloads/ShpZip/parcel.ZIP.

The calls were categorised using a string matching algorithm from the field Problem, e.g., if Problem contains the string `"Armed Encounter"` then `calltyp=violence`. To select types of crime that are most relevant for examining deterrence we focus on a subset of calls from the following categories: `'violence', 'theft','burglary', and 'disturbance'.` (The temporal distribution of the relevant calls (for detecting deterrence) is similar to that of all crimes (see Figure 2).

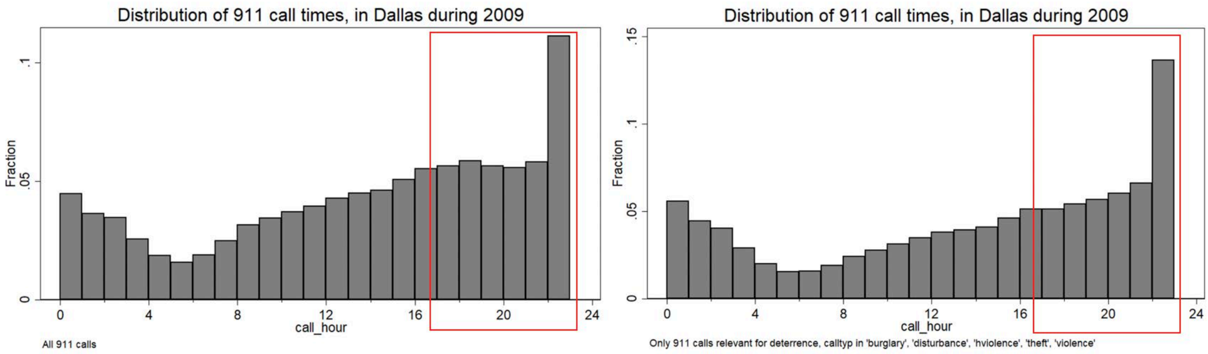

Figure 2: Distribution of 911 call times by hour for (a) all 911 calls, and (b) the relevant to deterrence call types (calltyp in one of these categories: 'burglary', 'disturbance', 'hviolence', 'theft', 'violence'). Calls between 17:00-23:00 were used for the analyses (marked with a red rectangle).

2.2 Estimating 911 calls hotspots

To establish a spatial pattern of 911 calls (Figure 3), we applied Kernel Density (KD) estimator with a radius R = 200m to all calls between 17:00-23:59 for the time period between June 01 - September 31 using ArcGIS (ESRI Inc., 2016).

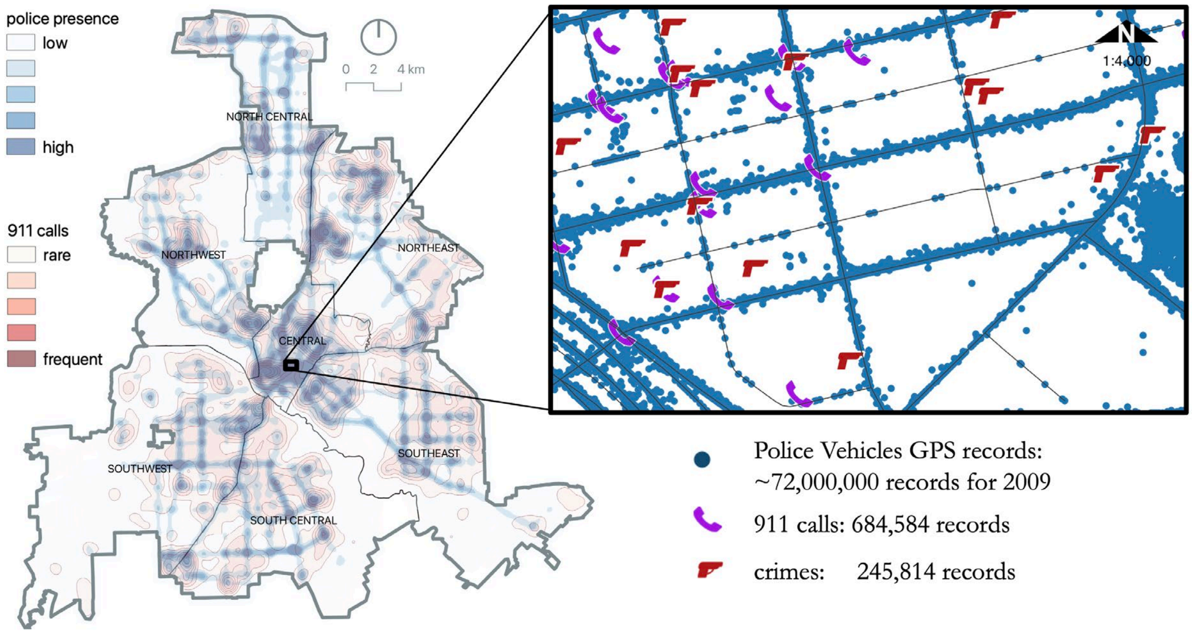

Figure 3: Close view of the crime and PVL data and KD estimates of the number of calls and police locations with division boundaries. Note that the crime hotspots not necessarily coincide with high police presence.

The output map is constructed at resolution 20 m and the bins are based on the histogram of the number of calls from the cell (Figure 4a): To represent the number 911 requests we have chosen the 99th, 95th, 75th, 50th and 20th percentiles of this histogram as boundaries of 6 bins. The resulting area A has the highest request rate of 44+ calls per cell, B is characterised by 24-43.99 calls per cell, C by 10-23.99 calls per cell, D by 5-9.99 calls per cell, and E by 3 – 4.99 and F by less than 3 calls per cell. A-F areas can be recognised in each of the seven Dallas divisions: North-Central (NC1), North-West (NW1), North-East (NE1), Central (C1, downtown), South-West (SW1), South-Central (SC1), and South-East (SE1).

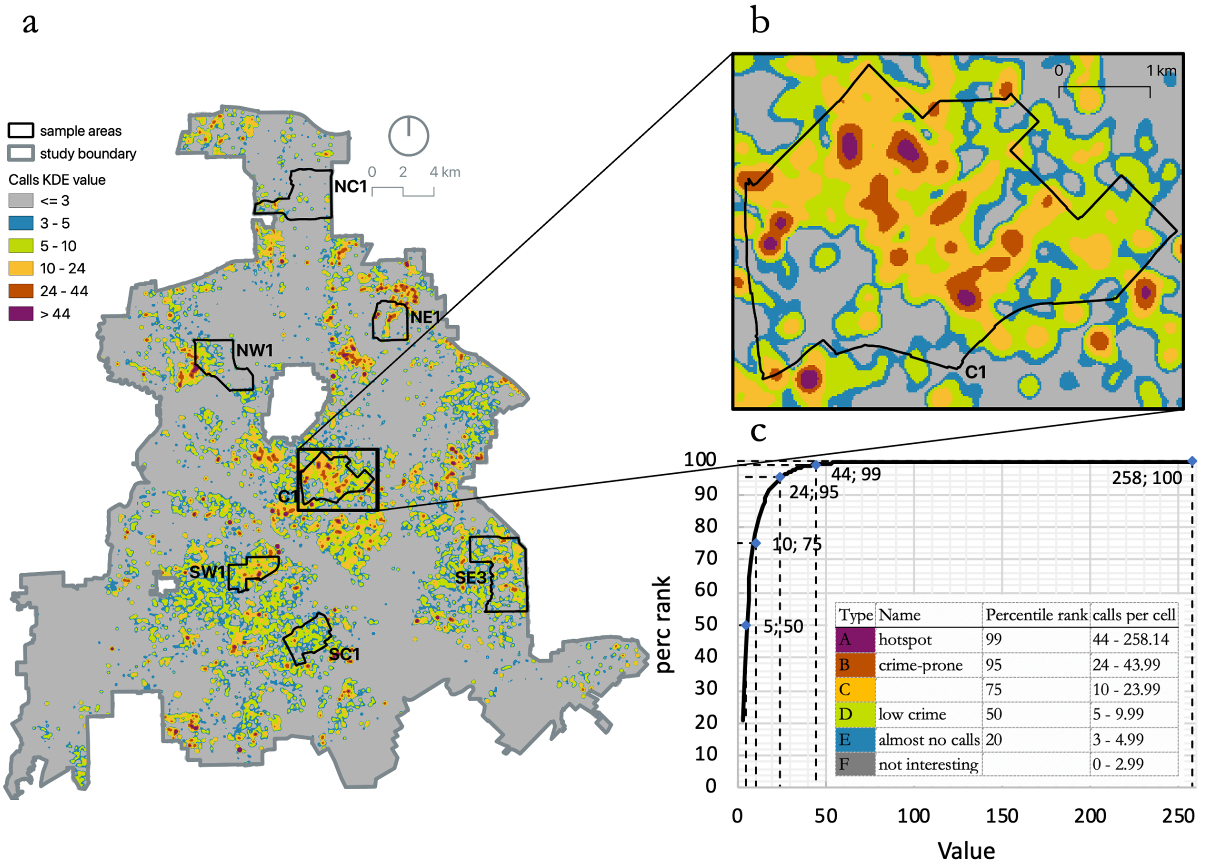

Figure 4: The cumulative histogram for the number of calls per cell and the boundaries of established bins (c) The KD estimates (R=200, cell size 20m) of the number of 911 calls of all types for the entire city of Dallas between June 01 – September 31, 2009, at time 17:00 < t < 23:59:59 (a,b).

To match between KD raster output and lots the following GIS operations were performed: (1) KDE raster was constructed in ArcMap (ESRI Inc., 2016) using the input of 911 calls points layer from PostGIS (PostGIS Project, 2017), after testing for different radii and cell sizes and selecting the R=200 with cell-size = 20m; (2) convert the KDE raster to points; (3) perform many-to-one spatial join between the polygon layer of lots and point layer of KDE using within spatial join with merge rule=minimum; (4) and lastly binning the resulting values into A-B-C-D-E bins as mentioned above. Figure 5 presents this match for area C1.

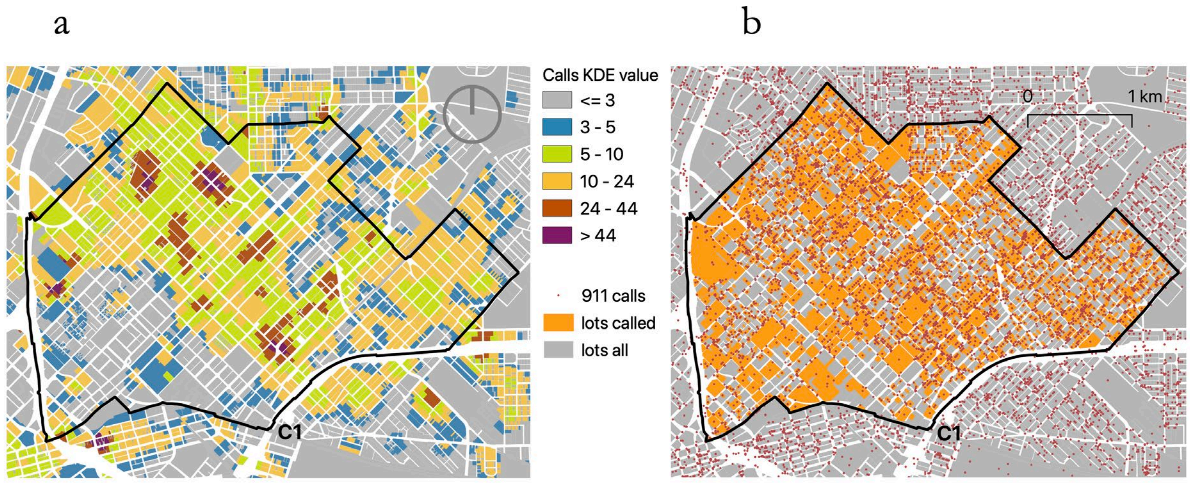

Figure 5: The downtown central sample area C1: Crime hotspots (a), All lots in grey and lots with 911 calls in 2009 in orange colour (b).

2.3 Matching instantaneous police presence and 911 calls

Our underlying assumption is that there might be a spatiotemporal mismatch between locations of police officers and the occurrence of crime at a fine spatiotemporal resolution that cannot be recognized based on the aggregate data. Figure 6 demonstrates the locations of crimes and 911 calls that are close in space but not in time. This mismatch is not observed when both police and crime are aggregated.

Figure 6: An example of the spatiotemporal mismatch between police and crimes. The first 911 call reporting criminal mischief happened at 19:11 (the green circle) and the police vehicle arrived at the scene at 19:29 (red line). Then a second 911 call about criminal mischief occurrs at almost the same location at 21:13 (red star).

To construct a measure of police presence leading up to the occurrence of a 911 call, we first filter out all vehicles travelling faster than 30 mph, the street speed limit in Dallas.[2] For patrol vehicles that drove slower than 30 mph we consider all patrol vehicles during the 10-minute interval *before* the call whose AVL pings were within a 1000m buffer of the area (see Figure 7 a), we estimate the minimal distance *between* the lot boundary of the call and *the closest vehicle*. One particular vehicle might be the closest car observed for several lots during a particular 10-minute interval (see in Figure 7b the trajectories of an example interval and in Figure 7c the resulting distances visualised as violet lines).

[2] Our assumption is that fast-moving police vehicles, such as the ones driving on highways, do not create deterrence.

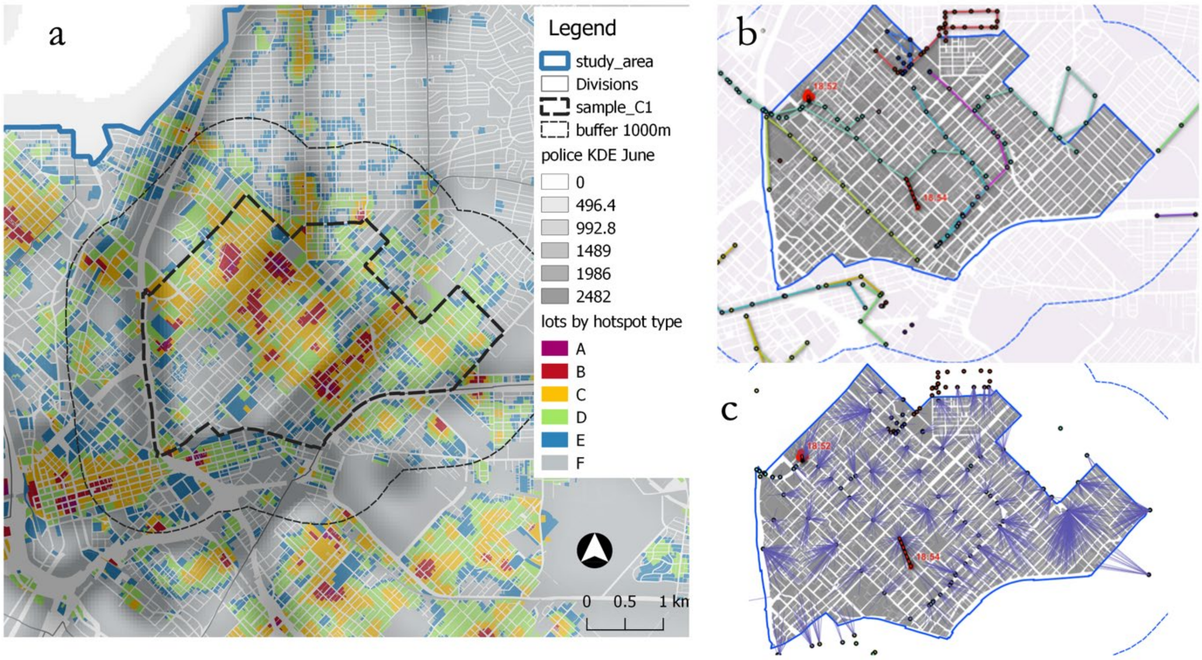

Figure 7: (a) Central division sample area C1 - lots by hotspot bin of 911 calls and police presence calculated based on police locations within 1000m buffer boundary (thin dashed line). (b) police trajectories in a 10-minute interval for example and (c) the resulting distances to closest police officer from each lot in those 10 minutes (violet lines).

2.4 Recognition of instantaneous deterrence

We define police presence as driving immediate deterrence if the probability of a crime at a certain location is lower when police patrol is closer to this location (red curve in Figure 8). Nagin et al. (2015) explain this deterrence effect is driven by the increased perceived risk of apprehension.

Using minimal distance between the police patrol during the 10 minutes leading up to the 911 call and crime location as an indicator of the patrol's closeness, we establish Crime Probability (CP) curves - the probability of crime as a function of the minimal distance between the patrol and crime location. We build this curve by distance d bins of 50 m: 0-50m, 50m-100m, etc, up to 600m and estimate probability of crime at a certain distance as

$$CP = p(d) = \frac{number\ of\ calls\ in\ case\ the\ police\ are\ at\ a\ distance\ d}{number\ of < lot, police\ vehicle > \ pairs\ at\ a\ distance\ d}$$

In what follows, we estimate CP curves by each of the A to E areas separately.

To facilitate statistical inference in regards to the CP curve we construct a no-deterrence CP curve. For this purpose, we randomly distribute the same number of 911 calls that served for construction of the CP curves, over the investigated area. Random spread of the call invalidates possible dependence of crime probability on the distance to nearest patrol car and enables us to estimate the amount of variance that would be necessary for a statistically grounded rejection of the deterrence hypothesis H0: Increased Distance to Closest Officer, Increases the Probability of Crime.

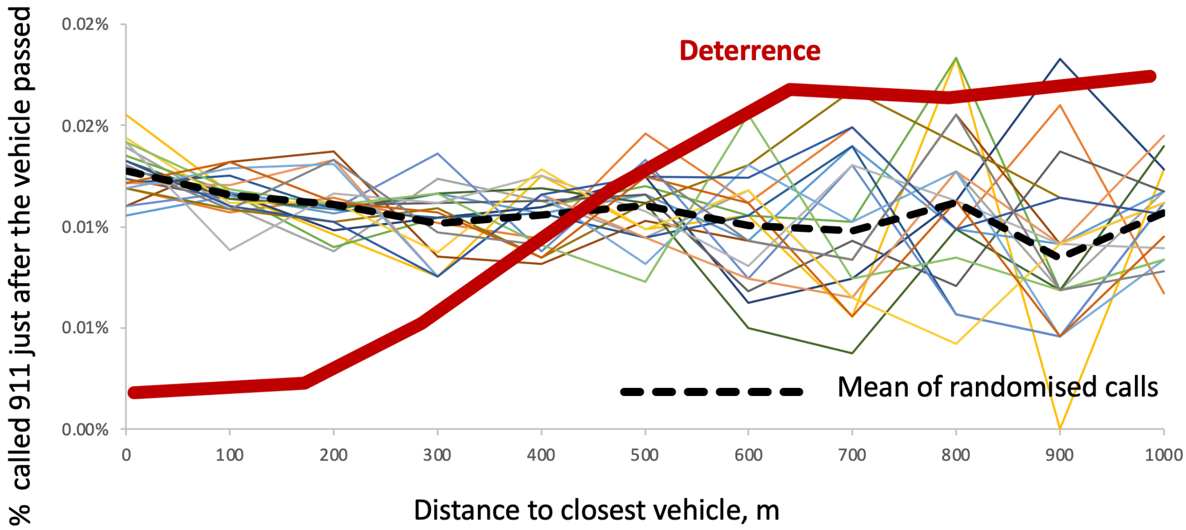

Figure 8: The hypothetical CP curve in case of instantaneous deterrence (Red), hypothetical no-deterrence curve (dashed) and the variance of the no-deterrence data (thick lines around no-deterrence curve) that is used for the statistical inference on deterrence.

3. Results

3.1 Equilibrium state of police presence in Dallas

In Figure 4, we graphically illustrate the prevalence of lots with different crime probabilities across Dallas, Texas. In Figure 9, we provide a color-coded mapping of not only the geographic spread of crime across the city, but also, the fraction of the population that resides in lots with crime propensitiesA – E. Only a very small proportion of lots in Dallas are defined as crime prone(reporting more than 24 calls in a 4 month period between the hours of 5 pm and midnight), roughly half of all crimes are derived from about 1/6 of the population, and 1/16 of the areas (Figure 9). This is in line with research by Weisburd (Weisburd, 2015) showing that 5% of street segments are responsible for 50% of crimes.

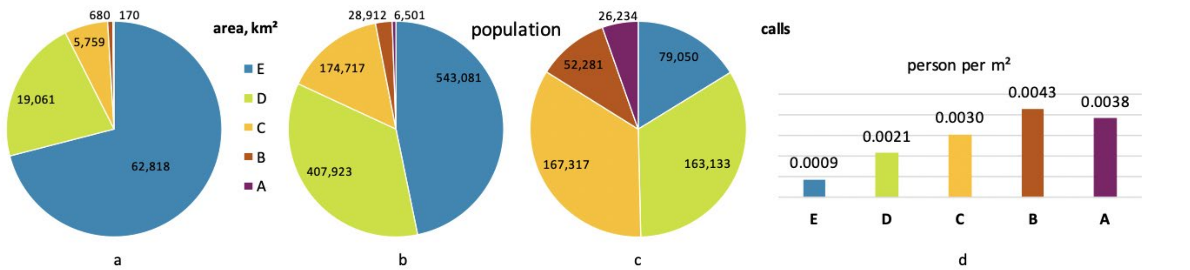

Figure 9: Area (a), population (b), number of calls (c), and population density (d), by areas A - E.

In Figure 10, we aggregate the data by crime propensity definition A-E and map out measures of criminal activity, reporting, and arrests. The top two figures demonstrate that measuring crime probabilities using both reported crime and 911 calls demonstrate similar relationships between area types A-E (Figure 10). However, figure c suggests that residence of high crime areas may be less likely to report a crime as every 3.39 calls result in a crime report in area A, with only 1.74

calls resulting in a crime report in area E. Residents of area A also seem to have to call almost double the number of times per incident that results in an arrest.

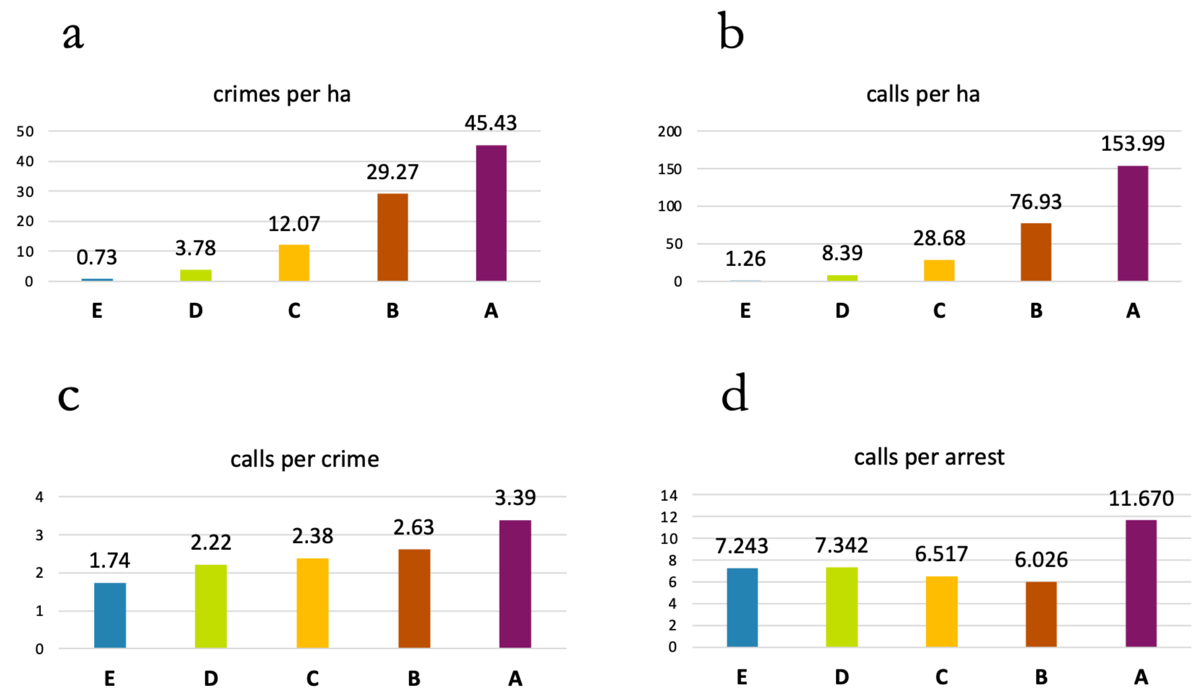

Figure 10: Number of crimes per ha, (a), calls per ha (b), calls per crime (c) and calls per arrest (d) for the A – E areas

High crime rates in areas A and B are correlated with higher average police presence and lower distances to closest officer – which could affect the general perception of "policing intensity" in the area in the long run (Figure 11 a,b). However, if there are plentiful crime opportunities in the vicinity, the higher police presence might not be enough to deter the perpetrators, which may be confirmed by lower police presence per reported crime (Figure 11 c).

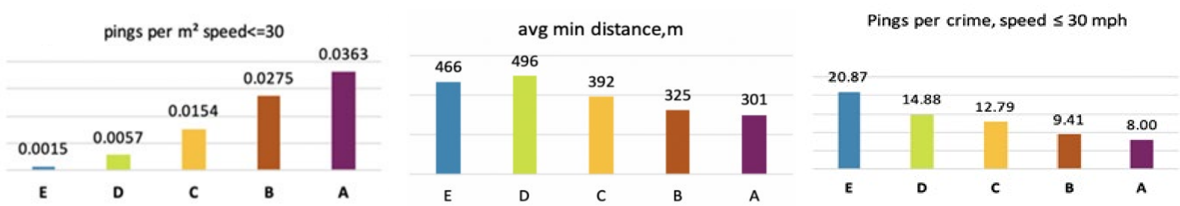

Figure 11: (a) Police presence per m² by crime frequency area type A-E, (b) mean distance to closest officer by area type A-E, and (c) police presence per crime by area type A-E. Note higher police per square meter but lower per crime.

In the long run, an equilibrium of higher police presence in more crime prone areas (per m², Figure 11 a) and closer mean distances to police (Figure 11 b) is established, but this increased level of police presence may not be sufficient to address the needs in crime hotspots (lower police presence per crime, Figure 11 c). This long-term emergent equilibrium might explain why hotspots remain hotspots, despite increased police presence. There is simply much more crime than the increased police presence can address. Additionally, figure 11-c raises the concern that police presence in high crime areas is primarily reactive (responding to reported crimes) as opposed to proactive (with a goal of creating deterrence). To focus on proactive policing, our analysis will examine the short-term deterrence response to police presence just beforehand. In other words, regardless of the average ratio of police per crime in the area, the perpetrators would still react to police presence at a given location if there exists short-term deterrence.

3.2 Short Term Deterrence

Figure 12 presents the CP curve for all 911 calls reporting crime in the Central division of Dallas during the entire observation period between 06/01/2009 – 09/31/2009. As can be seen, the trend of the resulting CP curve moves in the opposite direction of what we would expect iff deterrence was driving the relationship and is more in line with 'responsive policing' – more police in close proximity of crime prone areas:

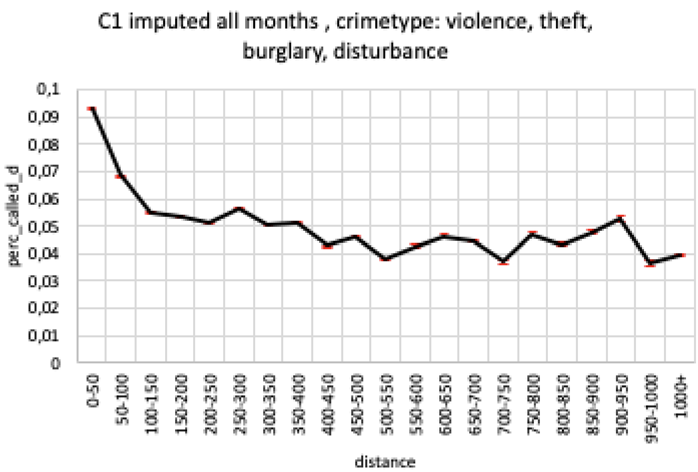

Figure 12: Percent of lots with 911 calls, located in C1 at each distance to closest police vehicle.

Figure 13, redraws the CP curve when focusing on areas with similar crime propensities across all Dallas divisions. The relationship remains similar even after the decomposition: at shorter distances the curve seems to point to responsive policing, while at larger distances there were not enough observations to draw a meaningful conclusion. The crime-prone area b (red line, Figure 13 b) doesn't point to either higher or lower crime frequency at shorter police distances. In all other areas the frequency of calls is higher at shorter distances.

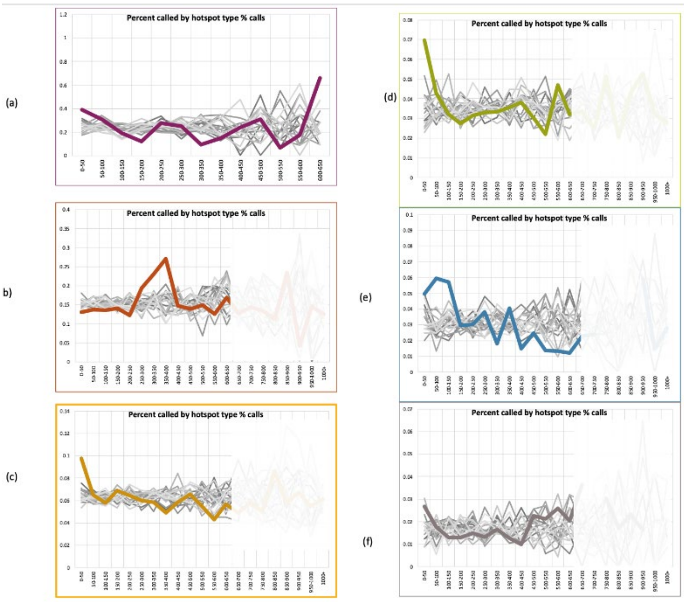

Figure 13: Crime probability curves by the level A-F of crime activity. The randomised call areas are shown in light grey in the background of each graph.

3.3 Can heterogeneous characteristics of parcels and time periods be driving our results?

Why would 911 calls be ***less*** likely to occur when officers are ***more than 100 meters*** away from a given parcel? To answer this question, we assess the magnitude of the difference in call probabilities between parcels where a police officer was observed at a 100 meter distance (H_{it}=0), versus parcels where the closest officer was farther away (H_{it}=1) for three linear probability models for a probability of a 911 call ($call_{it}$) at parcel *i* of $parcel\_type$ *A,B,C,D,E,F* in geographic reporting area *ra* during period *t*:[3]

$$equation\ 1{:}\ call_{it} = \beta_0 + \beta_1 H_{it} + \vartheta_t + u_{it}$$

$$equation\ 2{:}\ call_{it} = \beta_0 + \beta_1 H_{it} + \vartheta_t + \mu_{ra} + u_{it}$$

$$equation\ 3{:}\ call_{it} = \beta_0 + \beta_1 H_{it} + \vartheta_t + \mu_{ra} + \theta_{ra \times parcel\_type} + u_{it}$$

Where H_{it} is a binary variable that is equal to 1 if the closest officer is more than 100 meters away from a given parcel *i* during period *t* and 0 otherwise. The coefficient β_1 measures the average difference in call probabilities for a parcel where the closest officer is more than 100 meters away, relative to a parcel where there is an officer at the 100-meter mark or at an even closer distance. The variable u_{it} in equation (1) captures other unobserved factors that may vary across parcels that could impact the probability of a 911 call (number of people in the vicinity, characteristics of the population, etc.). We only include parcel time-periods where there was an officer observed within a 500-meter radius. For the larger distances the chance that the closest patrol car was beyond the area of analysis is essentially non-zero and increasing with the increase in distance.

[3] Reporting areas are the smallest geographic areas defined by the Dallas Police Department. On average, a reporting area contains roughly 182 parcels. *Parcel_type* defines the density of calls at parcel *i*.

In order to test the hypothesis that β_1 is statistically significant from zero, it is necessary to calculate standard errors for the estimated β_1 that account for the non-random sampling observed in the data. We do this by clustering standard errors at the parcel level. Instead of assuming that the variance of the error term (u_{it}) in the call equation (equation 1) is constant for each sampled observation and uncorrelated with other observations, we allow for correlation across observations recorded from the same parcel. This is especially important when working with large datasets where traditional analysis techniques often underestimate the size of the standard error.

In equation (1), we run our most basic analysis when including time fixed effects θ_t, which capture the impact of different time periods on the probability of a call, e.g., a call may be more likely when people are back from work than in periods when they are still at work. However, there are other factors included in u_{it} in equation (1) that are likely to vary across different locations (e.g., underlying crime risks such as gang activity, residential/urban area) and these same characteristics may be correlated with distance to closest officer, e.g., if less officers are on patrol in areas with lower crime risks this could impact our estimate of the coefficient of interest β_1. We address this in equation (2) by running our analysis when including geographic reporting-area fixed effects μ_{ra}, which controls for the fact that each parcel *i* resides in a reporting-area with different characteristics that impact the probability of a 911 call, e.g., a reporting area with gang or drug activity, or a reporting area that is located in a very popular/unpopular area. In equation (3), we provide a more accurate fixed effect for the underlying crime risk at a given parcel within a reporting area by including an interaction term between the reporting area fixed effect and the parcel type. This relates directly to the literature on location based hot spots that maintains that high crime areas are often concentrated at very specific locations (e.g., parcels) as opposed to larger geographic areas (e.g., reporting areas).

In column (1) of Table (1) we present the parameters' estimates for equation (1) that assumes that the distance of the closest officer from any given parcel is random across locations. Consistent with our earlier results, we find that when an officer is ***farther*** away from the parcel it ***decreases*** the probability of a 911 call by 0.012 percentage points, with the s.e. of 0.001. Because the average probability of a call is 0.02, this implies a significant 79 percent decrease in the probability of a call when officers are located farther away from the parcel. While this measured effect shrinks by about 25% when including reporting area fixed effects, it still remains significant at the 1 percent level, see estimates from equation (2), Table 1, column (2).

Column (3) of Table (1) presents the parameters' estimates for equation (3). As can be seen, the results in this case are much smaller than the results obtained with equations (1) and (2), and suggests that while heterogeneity in police availability across parcels can explain some of the 100-meter reactionary response, it cannot explain the entire effect. When focusing on parcels of the same type (*A,B,C,D,E,F)* within the same reporting area, we continue to find a significant difference in the probability of a call when officers are located more than 100 meters away from the parcel (a 36% decrease in the probability of a call).

Table 1: The dependence of 911 call probability on Officer Proximity

	All Parcels (1)	(2)	(3)
Distance > 100 Meters (Coefficient β_1)	-0.00012*** (0.00001)	-0.00009*** (0.00001)	-0.00005*** (0.00001)
P-Statistic	0.000	0.000	0.000
Time Fixed Effects[1]	Included	Included	Included
Reporting Area Fixed Effects[2]	Not Included	Included	Not Included
Reporting Area X Parcel Type Fixed Effects[3]	Not Included	Not Included	Included
Observations	27,247,209	27,247,209	27,247,209
Fraction of Parcels with Call (call_bar)	0.0002 [0.0123]	0.0002 [0.0123]	0.0002 [0.0123]
Percent Change in Call Probability (β1/call_bar)*100	-79%	-60%	-36%

Standard errors are presented in parenthesis and clustered at the parcel level. Standard deviations appear in brackets. An observations is defined by a parcel and ten minute time interval.

[1]Time fixed effects include controls for hour of day, day of week, and month fixed effects.

[2]Reporting areas are the smallest geographic area defined by the Dallas police department. The 11,587 lots included in our analysis our spread across 117 geographic reporting areas.

[3]Reporting AreaX Parcel Type provides a further control for the underlying crime risks across parcels of different types (hot spot, crime-prone, mid-crime, low-crime, almost no calls, minimal calls) within the same reporting area.

*Significant at 10%; **significant at 5%; ***significant at 1%

We further examine this result in Table 2, by running the equation (2) analysis separately on each of the crime frequency zones. Table (2), demonstrates that our results are robust across locations, suggesting that calls are 28 to 45 percent less likely to occur at parcels when police officers are located farther away. We measure the weakest effect in Zone A, those parcels that are defined as hot spots.

Table 2: The dependence of 911 call probability on Officer Proximity by crime zones

	Zone A (1)	Zone B (2)	Zone C (3)	Zone D (4)	Zone E (5)	Zone F (6)
Distance > 100 Meters	-0.00025 (0.00017)	-0.00016*** (0.00006)	-0.00009*** (0.00003)	-0.00004** (0.00002)	-0.00003 (0.00002)	-0.00003** (0.00001)
P-Statistic	0.139	0.006	0.003	0.03	0.124	0.049
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Reporting Area Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	174,890	1,055,044	5,309,926	7,948,443	4,206,511	8,552,395
Baseline Probability of a Call	0.0016 [0.04]	0.00056 [0.024]	0.00025 [0.016]	0.00012 [0.011]	0.0001 [0.01]	0.00006 [0.008]
Percent Change in Call Probability	-16%	-28%	-34%	-30%	-36%	-45%

Standard errors are presented in parenthesis and clustered at the parcel level. Standard deviations appear in
An observations is defined by a parcel and ten minute time interval.
*Significant at 10%; **significant at 5%; ***significant at 1%

In addition to heterogeneity across zones, we test heterogeneity across crime types. We might expect deterrence or reactionary policing to be more prevalent for certain types of crimes than others. Table 3 suggests that reactionary policing is most prevalent for theft & violent crime, where having an officer more than 100 meters away decreases the probability of a theft by 58 percent and a violent crime by 40 percent. However, car accidents, which are much less prevalent in the data than violent crime, may fall under the category of deterrent policing. Specifically, we find that when officers are located more than 100 meters away from the parcel the probability of a car accident incident *increases,* but this estimate is very noisily measured.

Table 3: The dependence of 911 call probability on Officer Proximity by crime type

	Violent Crime (1)	Burglaries (2)	Public Disturbances (3)	Theft (4)	Car Accidents (5)	Other (6)
Distance > 100 Meters	-0.00036*** (0.00009)	-0.00032* (0.00018)	-0.00024*** (0.00008)	-0.00055** (0.00026)	0.00012 (0.00019)	-0.00025*** (0.00008)
P-Statistic	0.000	0.084	0.003	0.035	0.518	0.002
Time Fixed Effects[1]	Yes	Yes	Yes	Yes	Yes	Yes
Reporting Area X Parcel Type Fixed Effects[2]	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,581,710	303,102	1,362,717	189,684	163,871	1,492,522
Percent Change in Call Probability	-40%	-34%	-26%	-58%	14%	-28%

Standard errors are presented in parenthesis and clustered at the parcel level. Standard deviations appear in brackets.
An observations is defined by a parcel and ten minute time interval. The fraction of parcels with a call is 0.0009 (s.d. 0.03)
[1]Controls for hour of day, day of week, and month fixed effects.
[2]Reporting Area X Parcel Type control for the differences in underlying crime probabilities across parcels of different types (hot spot, crime-prone, mid-crime, low-crime, almost no calls, minimal calls) within the same reporting area.
*Significant at 10%; **significant at 5%; ***significant at 1%

4. Conclusions and Discussion

When examining lot-level micro data, we find no evidence of a linear relationship between police proximity and 911 call outcomes. The raw data suggests a 100-meter reactionary effect, where there is a higher probability for a 911 call specifically in parcels with officers very close by (within a 100-meter radius). This result is fairly robust across locations and crime types.[4]

Why would reactionary policing be so prevalent in this data? Recall that Dallas Police Department implements a hotspots-policing strategy that is observed in the data. Thus, ***police presence*** is highest in high crime zones. However, Figure 11 demonstrates that ***per call/per crime***, police presence is actually ***lower*** in hotspots. The police-established equilibrium during the period of study (2009) has higher police presence per area for crime-prone hotspots, yet it is insufficient for equal policing per call/crime. Thus, for example, in hotspots even if there is a policeman on every corner, that might not be enough to create deterrent policing which addresses the larger probability of crimes in saturated areas. This could be what is driving the reactionary policing relationship that we observed in our analysis. In an environment where higher crime rates drive higher levels of police presence, this paper suggests that observing more police at more crime prone areas may not be enough to drive deterrence.

A promising direction for future research would be to examine the long term policy implications of 911 call incidents on proactive policing. While we might expect the immediate impact of a 911 call to be reactionary - an increase in police presence followed by a return to the level of policing saturation that was observed prior to the event, after a certain number of incidents police presence might be adjusted to reflect the change in the policing needs of that location. These data could provide a unique opportunity to examine this intersection of short and long term policing goals across different communities in Dallas.

[4] We also tested alternative KDE radii of 100, 200, 500, 1000m and several cell sizes, but the results were very similar to those presented in the text.

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