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Measuring the Spatial and Temporal Patterns of Police Proactivity

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Abstract

Objectives To measure where officers engage in proactive, self-initiated activities, how much time they spend being proactive, and whether their proactive activities coincide with crime patterns.

Methods This study uses Andresen's Spatial Point Pattern Test to compare the spatial similarity between police proactivity and crime, as well as regression modeling to explore the relationship between proactivity and crime and the time spent on proactivity and crime.

Results In the jurisdiction examined, high levels of proactivity are noted. This proactive activity is more likely to occur in places where crime is most concentrated. Additionally, the number of proactive calls and the proactive time spent per crime-and-disorder call remain high and stable across spatial scales. For each crime call received at a street block, police initiated 0.7 proactive activities and spent approximately 28 min carrying out proactive works.

Conclusions This study develops a way of measuring proactive activity by patrol officers using calls for service data. We find that not only do officers in this jurisdiction exhibit higher levels of proactivity to prevent crime (compared to reacting to crime), but they also do so in targeted, micro-place ways. Agencies may consider using similar techniques to gauge the levels of proactivity in their agencies if proactive activity is a goal.

Keywords Policing · Proactivity · Non-committed time · Place-based policing

Introduction

In the last four decades, some police agencies have shifted their interest from being primarily reactive and enforcement-oriented to being more proactive and preventative. This proactivity includes a wide gamut of activities intended mostly to prevent and deter

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crime and recidivism, but also to build citizen and community relationships that improve police service delivery, trust, and confidence. Such activities are now well-known innovations, such as problem-solving, intelligence-led policing, directed or "hot spots" patrol, community policing, focused deterrence strategies, and even the use of procedural and restorative justice strategies. Also included as proactive policing are more controversial approaches, such as the use of misdemeanor arrests to combat low-level crimes and disorder, as well as the use of pedestrian stops, field interviews, traffic enforcement and stop-question-and-frisk. Although the scope and variety of proactive strategies make it hard to succinctly define or categorize proactive policing, it is often contrasted with reactive policing, or the "standard model" (see National Research Council 2004; Ratcliffe 2008; Weisburd and Braga 2006). These more traditional approaches to policing tend to emphasize adherence to procedures and general orders, rapid response to calls for service managed by a computer-aided dispatch system, case-by-case investigations, and enforcement and arrest.

Researchers and their law enforcement partners have amassed a great deal of research evidence that generally supports the effectiveness of proactive interventions, with some important caveats. For example, studies have shown that police can prevent crime by focusing their efforts at high-crime places (see Braga et al. 2012; National Research Council 2004) without necessarily displacing crime (Weisburd et al. 2006). Specific evaluations that focus on hot spots of drug markets (Weisburd and Green 1995), gun crime (Sherman and Rogan 1995), crime and disorder (Braga and Bond 2008), or violent crime (Ratcliffe et al. 2011) show that police can be effective when they proactively target these types of problems at specific places. In their review of problem-oriented policing, Weisburd et al. (2010) find that experimental and quasi-experimental studies show that problem-solving by the police has an overall modest yet statistically significant impact on crime. Similarly, Braga and Weisburd (2012) conclude that focusing deterrence efforts on high-risk individuals and repeat offenders in proactive and problem-oriented ways can be effective. It should be noted that there is much less research on the impact of police proactivity on other important outcomes, such as police legitimacy or citizen reactions to police activity. However, it is fair to say that we now know that when police are proactive and tailored in their efforts, targeting risky places, people, and situations, they can avert and reduce crime (see reviews by Lum et al. 2011; Nagin et al. 2015; National Research Council 2004; Weisburd and Eck 2004; Sherman and Eck 2002).

However, despite both growing interest in, and evaluations of, proactive policing, we know much less about the actual prevalence of proactivity in police agencies. Simply asking agencies whether they use community policing, problem-solving, or hot spot policing, as have some of the national law enforcement surveys, is inadequate in understanding the extent to which proactivity is used or how proactivity manifests itself in any given agency. We know that officers have periods in their shift that are not spent on responding to calls for service, making arrests, or carrying out other administrative duties. This "uncommitted time," as Kelling et al. (1974) described it, is the time in which we might expect police officers to be proactive. However, empirical studies indicate this time can be as much as 37–86 % of a patrol officer's shift (Famega 2005) and officers have a great deal of discretion as to how they use this time. Measuring proactivity is further confounded by the lack of reporting of proactive activities when they are carried out. Police agencies still rely on information collection and technology systems that support the standard model, and they prioritize the recording of reactive activity (response to calls for service, arrests, investigations), not proactive activity. Some systems may capture clues regarding the amount and type of proactive activity in which an officer engages. For example, there are certain proactive (i.e., self-initiated) activities that police officers regularly report to dispatch for purposes of officer safety and documentation. These might include pedestrian and car stops, investigative follow-ups, or business checks. Some agencies might ask officers to fill out "run sheets" in which they might record carrying out proactive foot patrol or preventative patrol at a particular location. Other proactive activities may be captured in technology systems such as automatic vehicle locators (see Weisburd et al. 2015). However, this recording of proactivity not only varies across agencies, but also shifts, units, and individual officers. Given the push towards proactivity, finding ways to accurately measure it is critical for further evaluating proactive strategies and also measuring their performance in practice. In this paper, we provide one methodological approach and bring greater attention to investigating the relationship between police proactive efforts at places with high levels of crime.

Measuring Proactivity: The Current Study

One fruitful source of proactivity collected by police agencies is calls for service data. Although far from perfect (see Klinger and Bridges 1997), calls for service (CFS) data, as captured by computer aided dispatch (CAD) and other records management systems, still provides the best understanding of what patrol officers are doing minute-by-minute during their shifts. While a great deal of officer and detective activity is never recorded in an official crime or arrest report, CFS/CAD information systems do record a large proportion of this activity. Some of this reporting occurs because officers need to let the dispatch and others know where they are and what they are doing for officer safety concerns. For example, an officer who decides to proactively approach a pedestrian or vehicle on the street may use their hand-held radios or in-car mobile computers to tell the dispatcher where they are and what they are doing. They may not record what happened during the stop (especially if no further action is taken) or what motivated them to carry out the stop in the first place. However, the location and time are recorded. At the same time, if they don't feel safety is a concern, they may not report when they are proactive. Indeed, there are likely reporting biases in which activities they report to their dispatchers and which they do not. Activities such as hot spot patrol, business checks, community meetings, or investigative follow-ups with citizens, may not result in any alert to the dispatcher or fellow officers. Problem-solving activities, including engaging with crime analysts or devising problem-solving action plans may also go unreported. Specialized units which engage in proactive activities will likely not engage with dispatchers at all, unless, again, they feel their safety might be compromised. However, CFS data still remains one of the best sources of information to reconstruct how officers use their time, for both proactive activities, as well as the recording of crime and disorder (including those crimes that for one reason or another are not further officially reported).

Using CFS/CAD data, we seek to answer two questions relevant to our broader interest in proactivity. First, do police tend to concentrate their proactive behavior in places with high levels of crime, given that we know this helps prevent crime? If a police agency is prioritizing prevention and proactivity, we might expect police proactivity and crime concentrations to exhibit consistent spatial patterns, and perhaps at very specific places. The second research question follows from the first—are police officers also spending more time doing proactive work in places that have higher levels of crime? While we might expect officers to spend more time in places with high levels of crime, the opposite might also be true. Police officers might spend *less* time doing proactive work at crime hot spots if most of their time is spent answering calls for service in those hot spots.

Alternatively, the amount of time spent proactively at high-crime places might be higher at places that are mildly hot, but then decrease at those hottest locations, thus exhibiting a curvilinear rather than a linear relationship. Such a curvilinear relationship may indicate inadequate resources being available at places with the highest levels of crime.

To try and measure spatial and temporal elements of proactivity, we specifically analyze CFS data from the Jacksonville, Florida, Sheriff's Office (JSO). The JSO is an urban sheriff's office with more than 1500 sworn officers serving a densely populated city.[1] We believe the JSO has had a high level of commitment to proactive, problem-oriented, and evidence-based policing since at least the early 2000s. The agency has an advanced crime analysis system, which was developed in 2002 and which at the time of this study was an integral part of the agency's patrol, investigative, and management systems. The agency's leadership, as well as the crime analysis unit, have been nationally recognized for their innovation in the use and integration of advanced crime analysis in the agency's operational decisions. At the time of this current study, the crime analysis unit had already developed systems to find, systematize, collate, manage, and analyze data, and had also found ways to use that data for patrol and investigative purposes. The crime analysis unit was also integrated into the agency's problem-solving specialized units as well as its investigative units. Existing quantitative and qualitative studies of this agency showed the JSO as willing and able to carry out proactive policing activities, evaluations, and innovations (see Groff et al. 2015; Harris Corporation and the Jacksonville Sheriff's Office 2002; Taylor et al. 2011), and that proactivity is a concept that officers and specialized units are familiar with (see Koper et al. 2015).

Data and Sample

JSO's CFS/CAD data is ideal in studying proactive policing as it distinguishes when officers initiate a record in the CAD versus when a citizen does (through the 911 system). When citizens call the police and an officer is assigned, the call is flagged with the words "PHONE" or "911." When a police officer initiates any activity that is not prompted by a citizen call for service, this is recorded in the data as "MDT" (mobile computer unit) or "OFFICER." Recorded for almost all of these events were the location and time duration of the call. In 2013, 888,960 total records were in the agency's computer aided dispatch system. Of these, 57 % were labeled as citizen-initiated and 43 % were initiated by the police. Note that some of the citizen-initiated calls for service may not be related to crime, and some of the officer-initiated calls may not be proactive in nature. We removed such calls, a process discussed shortly. However, we note that the JSO calls-for-service data, compared to similar data from other agencies analyzed by the second author, provided some of the best clues as to where, when, for how long, and for what situations officers were proactive as well as reported crime and disorder events, including those events that may not lead to an officer making an official report of an incident. We used the calls-for-service database for both our measure of crime (citizen-initiated calls) and proactivity (police-initiated events).

[1] The city's population estimate is 853,328 based on 2014 census information, and is predominantly white, with blacks representing about a third of the population, and other racial and ethnic groups accounting for only small shares. The census shows that 17.3 % of the city's population live below the poverty line, and the city has high rates of crime compared to the average of other cities with similar populations. Visit http://quickfacts.census.gov/qfd/states/12/1235000.html for more information.

As already mentioned, not all records in the computer aided dispatch system are relevant for this analysis, and therefore were excluded. For instance, address information was missing in 18 % of the records, and time information was missing for 106 cases. Because both spatial and temporal information were needed to conduct this study, we excluded these records (see footnote 3 for an analysis of all excluded records). 1.7 % of all of the records were also excluded where the recorded address was likely not the location of the event, but instead a well-known magnet for crime reporting, such as a police station, hospital, or detention center. There were also 1116 cases that did not indicate if they were citizen or police initiated, which we excluded. We also excluded police-initiated records in which an arrest was made, a mere 1.7 % of all calls-for-service records. We decided to exclude these cases because the time span of arrest activity is tripled by administrative processes, and the officer is also no longer likely to be at the location.[2] While we recognize that some of these arrests might have resulted from proactive activity, the long time periods could skew our temporal analysis of how much time officers were actually engaged in the proactive activity.

We excluded several types of calls that are not commonly regarded as crime, disorder, or proactivity. To do this, we categorized each remaining record as one of 10 types: violent crime, property offenses, disorder incidents, offenses of drugs and vice, suspicious incidents, traffic-related offenses, investigations, administrative duties, service-related activities, and other non-crime events (e.g., “unverified 911” and “meet hospital”). We then labeled as “crime and disorder” those *citizen-initiated* calls for violence, property crimes, disorder, drug/vice offenses, and suspicious incidents. Our measure of “proactivity” included all *police-initiated* calls for any of these activities except those labeled as administrative and other non-crime calls which were excluded. We made one exception and included the small proportion of police-initiated administrative activities that were labeled as “special assignment,” which could include proactive problem-solving or hot spot targeting, according to the JSO.

Finally, as the study’s goal was to understand the spatial and temporal patterns of police proactivity at places with higher amounts of crime, only those calls in which recorded addresses could be geocoded (assigned to a latitude and longitude coordinate) were retained. For the current dataset, 234,660 citizen-initiated cases (93.2 %) and 235,455 police-initiated cases (85.2 %) were geocodable, which are considered acceptable rates (Ratcliffe 2004). The lower proportion of geocodable records in the police-initiated data is expected. Calls for service from citizens and victims more often specify an actual address that is amenable to geocoding as opposed to potentially less detailed location descriptions given by officers (e.g., “I’m at the intersection of Main and Elm”). The final dataset, with 234,660 citizen-initiated cases (crime), and 235,455 police-initiated cases (proactivity), continues to show that after excluding cases not relevant in this analysis, a large proportion (about half) of JSO activities are proactive in nature.[3]

[2] The average time spent on each police-initiated case with arrest is 112 min, while the average time for police-initiated cases in our final sample is 38 min.

[3] After excluding events from our analysis, we analyzed the excluded events. Traffic-related events accounted for over 30 % of the data excluded from the analysis, followed by events labeled as “administrative issues” (17 %). Both of these categories were overrepresented in the excluded data compared to the original data. This is likely due to traffic-related cases lacking address information (60 % of excluded cases were traffic-related). Further, nearly all administrative cases (with the exception of those marked “special assignment”) were excluded as they could not be considered either crime or proactivity. Finally, the *non-crime* category was also overrepresented in the excluded data for the same reason. All of the other categories of events were underrepresented in the excluded data.

Table 1 shows the breakdown of the final sample of citizen-initiated crime and disorder events and police-initiated proactive events by event type. Also included in Table 1 is the average time spent on each type of proactive activity. Notice the variation in the types of officer-initiated calls compared to citizen-initiated calls. Violence and property crimes make up a small proportion of officer-initiated proactive calls, but often take up more time. More frequently, officers initiate investigations, non-administrative service activities, proactive traffic stops, and activities related to suspicious incidents or disorders.

Methods of Analysis

To examine our first question—the spatial correlation between police proactive work and the location of crime (i.e., citizen-initiated calls for service)—we use Andresen's Spatial Point Pattern Test (SPPT) at various spatial levels, a repeat-sampling test that measures the similarity between two spatial point patterns at the local level. SPPT was developed by Andresen (2009) to test and visualize whether and to what extent two geographic patterns are similar at selected spatial levels. This model advances spatial analysis, which primarily analyzed the spatial patterns and autocorrelation of a single geographic pattern (see discussions of this issue by Lum 2008).

Andresen's SPPT treats each geocoded event as a point, and calculates the number of points falling within each spatial unit for both datasets. Next, it randomly and repetitively samples 85 % of points in one dataset 200 times. For each area in the dataset, SPPT calculates the percentage of events that have occurred in the area and then uses these percentages to generate a 95 % confidence interval by removing the top and bottom 2.5 % of all counts. Finally, it compares the 95 % confidence interval with the percentage of points in the other dataset falling within the same area and decides whether these two datasets are similarly distributed at that place. By comparing the percentage rather than the number of cases falling within spatial units, the SPPT controls for the differences regarding the number of observations between the two datasources.

The outputs of SPPT contain two parts. A global parameter—Andresen's S—indicates the overall similarity between two spatial point patterns. SPPT also produces an S-Index for each spatial unit of analysis. This S-Index categorizes the relationship between crime and proactivity in that spatial unit into one of three groups. A "+1" index indicates that the proportion of total *crime* that falls in that spatial unit is statistically significantly higher than the proportion of total *proactivity* that falls into that spatial unit. A "−1" indicates that the proportion of total *proactivity* that falls into that spatial unit is more than the proportion of total *crime* that appears in that unit. Finally, "0" indicates that there is no statistically significant difference between the proportion of proactivity and crime in that spatial unit. The S-Index is useful, as it provides a way of understanding the balance or imbalance in the amount of proactivity (or proactive time) that is spent in any given spatial unit compared to the amount of crime in that unit.

Deciding on the size of the spatial unit in which to run SPPT to determine the balance of proactivity and crime is both a theoretical and an empirical question. While the hot spots literature has established a solid case that targeting "micro" places can be effective in reducing crime (see Weisburd et al. 2012), police often are assigned to broader geographic areas (see discussion by Koper 2014). Given the exploratory nature of this study, we decided to examine the spatial similarity between crime and police proactive work at four of the different spatial levels available to us, including census tracts, block groups, and

Table 1 Categorization and distribution of citizen- and police-initiated calls for service ("crime" and "proactivity")

Description	"Crime"	%	"Proactivity"	%	Average time per case (minute)
Investigation: investigate, follow-up	–	–	96,781	41.1	46.3
Service: check individual/property, assist motorist, found property	–	–	81,334	34.6	21.2
Traffic-related incidents: traffic-related, crash, reckless driver, hit and run crash, drunk driver, hit and run	–	–	23,642	10.0	26.8
Suspicious incidents: suspicious person, alarm, prowler	60,400	25.7	12,959	5.5	25.3
Disorder incidents dispute, noise complaint, juvenile complaint, vandalism, mentally ill, animal, illegal parking, shoplifting, drunk, obscene/threat contact, abandoned vehicle, fireworks	104,450	44.5	8510	3.6	43.2
Special assignment	–	–	7367	3.1	191.9
Property offenses theft, burglary, forgery/worthless/fraud, auto theft, con	33,975	14.5	2885	1.2	81.4
Crimes of drug and vice drug investigation, prostitution	4264	1.8	1032	0.5	48.6
Violent, person, and weapon crimes domestic, assault, discharge firearms, fight, robbery	31,571	13.5	945	0.4	91.4
Total	234,660	100	235,455	100	39.6

As reactive as "investigate/follow-up" sounds, it could be a catch-all category and involves a wide range of police activities as suggested by our exchange with the police agency involved. For example, police may approach an individual on the streets, ask for information, and code such acts as "investigate". "Follow-up" can also be follow-up of previous proactive work. Admittedly such a category can indicate reactive works or citizen-initiated issues, but without further information, we would not know which part of the investigation is reactive or proactive. The only common feature that we do know for sure is that they are all generated by police officers. We agree that a more detailed data recording by patrol officers is called for, but at the current moment, we do not think those categories should be removed from the proactive analysis

blocks, as well as at the "street segment" level.[4] This approach aligns with a study by Andresen and Malleson (2011) in which they test the spatial similarity using the SPPT between different types of crime (e.g., violence and disorder) at various geographic levels (e.g., census tracts, dissemination areas,[5] and street segments). Doing so may also provide practical insights about the type of locations that police should deploy proactive activities within.

To examine our second research question—how much time police proactively spend at places and whether that time correlates with the distribution of crime—we use ordinary least squares (OLS) regression models. Given the underlying assumption of linearity in the OLS regression model and given that we hypothesized earlier that the amount of time

[4] In 2013, the city of Jacksonville had 174 census tracts, 490 block groups, 14,904 census blocks, and 54,832 street segments.

[5] The "dissemination area" is a small area composed of one or more neighboring dissemination blocks, with a population of 400–700 persons. All of Canada is divided into dissemination areas, which might be compared with census-block groups in the United States.

police proactively allocated at places might be curvilinear, we also test the linearity of this relationship. As with our spatial analysis, we examine the relationship between time spent on proactivity and crime locations at different spatial levels. However, one difference is that while we used street segments to examine the spatial relationship between citizen calls (crime) and officer proactive activity, we retained the hundred-block designation given to us by JSO for the temporal analysis. This reduced any additional error that would be incurred from re-geocoding data to a spatial unit of analysis not provided by JSO. Ideally, we would have preferred to use the hundred-block unit for the spatial analysis as well, but SPPT requires a spatial unit file that is not available at the hundred-block level.[6]

Results

Part I: Does Police Proactivity Correspond with Crime "Hot Spots"?

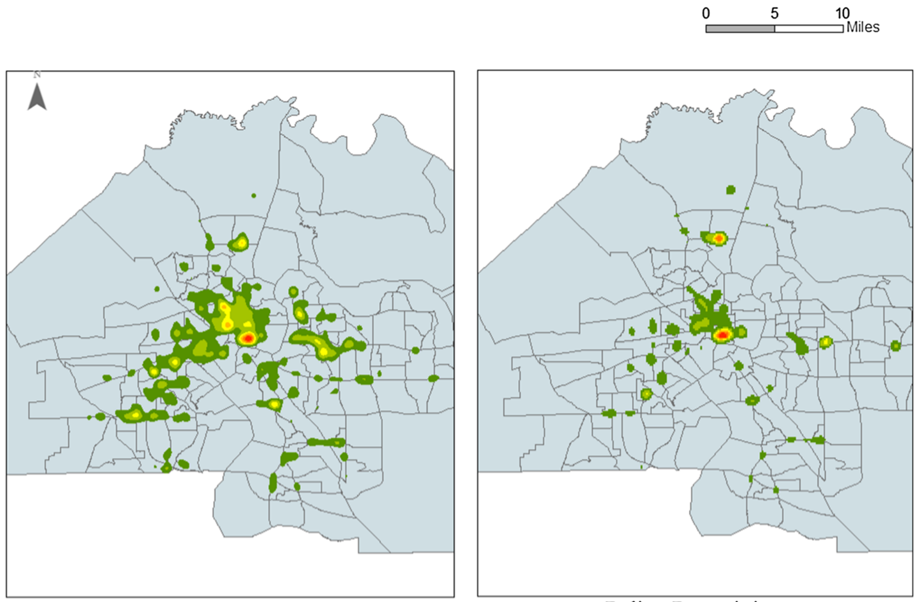
As in many other cities, crime and disorder calls in Jacksonville are highly concentrated. Figure 1 depicts the geographic distribution of citizen-initiated calls for crime and disorder and police-initiated proactive activities in Jacksonville in 2013 in kernel density maps. As illustrated, both crime calls and proactive activity concentrate in the downtown, central area of the city, with a number of meso-hot spots distributed sporadically in the rest area.

Table 2 shows Andresen's S, the similarity index of the spatial patterns in police proactive work and crime, at the census-tract level, the block-group level, the census-block level, and the street-segment level with and without removing the zero call cases. Andresen's S indicates that police proactive work and crime are similarly distributed in around 5 % of the census tracts and 5 % of block groups, and in around 44 % of the census blocks and 45 % of the street segments.

The increasing Andresen's S for smaller spatial units was also seen by Andresen and Malleson (2011) and may not necessarily indicate a greater efficiency in the matching of spatial patterns at smaller spatial units. Andresen and Malleson argue that part of the reason for this phenomenon is that the percentage of spatial units that have no crime increases when smaller units of analysis are used, which is also the case in our data. To address this issue, we follow Andresen and Malleson's suggestion of conducting a sensitivity analysis by dropping units with neither proactive events nor crime and disorder calls, and performing the SPPT again with only nonzero spatial units. The results are shown in the third column in Table 2. Similar to what is observed by Andresen and Malleson, the difference in the similarity indices among different spatial levels shrinks substantially, although the pattern of spatial consistency becoming more apparent at smaller units remains. These findings indicate that at smaller geographic units, there appear to be similar distributions of police proactivity and crime (as measured by citizen-initiated calls for service) in 10–15 % of these units.

Recall that in addition to the overall Andresen's S, SPPT also produces an S-Index for each spatial unit of analysis specified. Figures 2, 3, and 4 map the spatial pattern between

[6] Since the data were originally recorded at the hundred-block level, no spatial join process and thus no shapefile at the hundred-block level are required for the temporal OLS regression analysis. On the other hand, Weisburd et al. (2004) created a hundred-block shapefile based on the street database in Seattle. We did not adopt the same strategy for the Jacksonville street database, because house numbers associated with the odd and even sides of street segments tend to be inconsistent. For example, if we reorganize the street segment based on the house number on the even side in Jacksonville, we tend not to get consistent numbers on the odd side.



Crime
(a)

Police Proactivity
(b)

Fig. 1 Geographic distribution of call for service data using kernel density maps

Table 2 Andresen's S at various spatial units of analysis with and without zero cases

Unit of analysis	Andresen's S	Andresen's S, excluding zero
Census tract	0.0517	0.0462
Block group	0.0510	0.0452
Census block	0.4411	0.1498
Street segment	0.4455	0.1070

police proactivity and crime at the census tract, block group, and census block level. For each figure, the black areas show places where the amount of citizen-initiated incidents is significantly and proportionately greater than police proactivitity (positive 1). The gray areas show places with greater police proactivity than citizen-initiated crime incidents (negative 1). The white areas are places where no significant difference is observed (0).

At the census-tract level (see Fig. 2), police proactivity is proportionally higher than crime in 69 units, mostly at the central and the outer areas of the city. In between there are 96 black census tracts where crime is proportionally higher than police proactivity. Census tracts with the same levels of proactivity and crime are infrequently observed (nine tracts). These findings show that at the tract level, police proactivity does not often *proportionally* correlate with crime and disorder calls, but in 40 % of the census tracts the percentage of proactive events is higher than the percentage of crime and disorder events. We observed a similar pattern at the block-group level (see Figs. 3), a spatial level that can also be a meaningful unit of analysis (see e.g., Yang 2010). Block groups with similar percentages of crime and proactivity are the least frequent (25), indicating an overall low level of proportional similarity between two spatial patterns. More block groups (292) have levels of

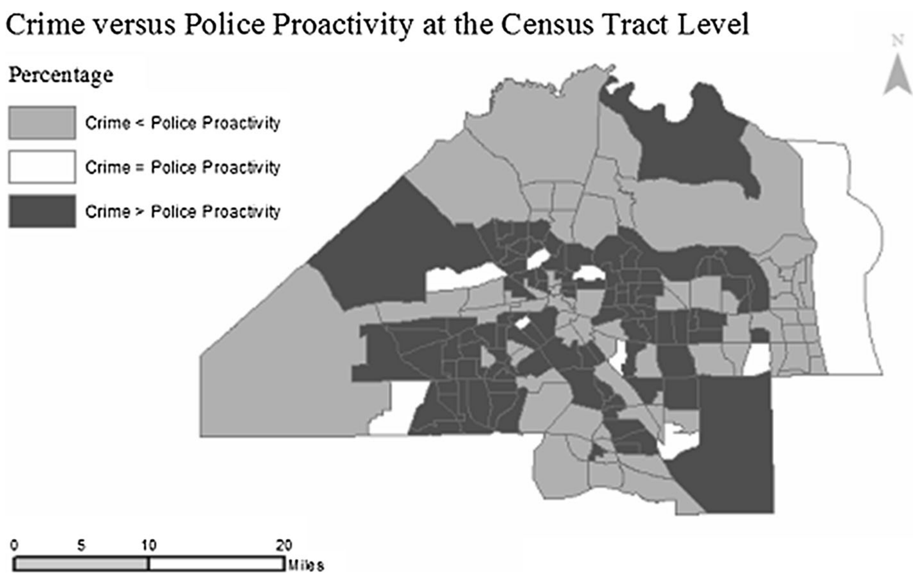


Fig. 2 SPPT map at the census tract level

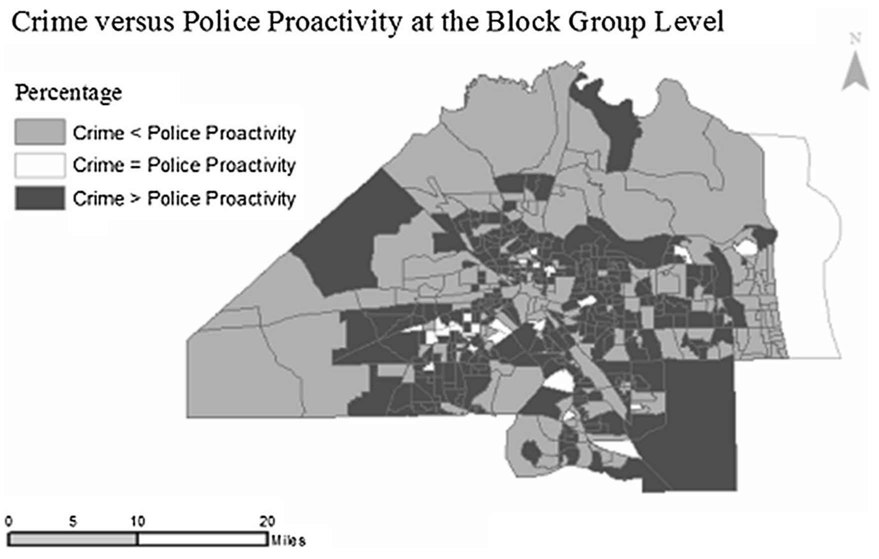


Fig. 3 SPPT map at the block group level

crime that are proportionately higher than police proactivity, compared to those that have a higher proportion of proactivity than crime (173). Again, these exploratory spatial findings do not imply that police in Jacksonville are not proactively allocating their resources to high-crime places. Indeed, for about 35 % of block groups in Jacksonville, police proactivity proportionately outnumbers crime.

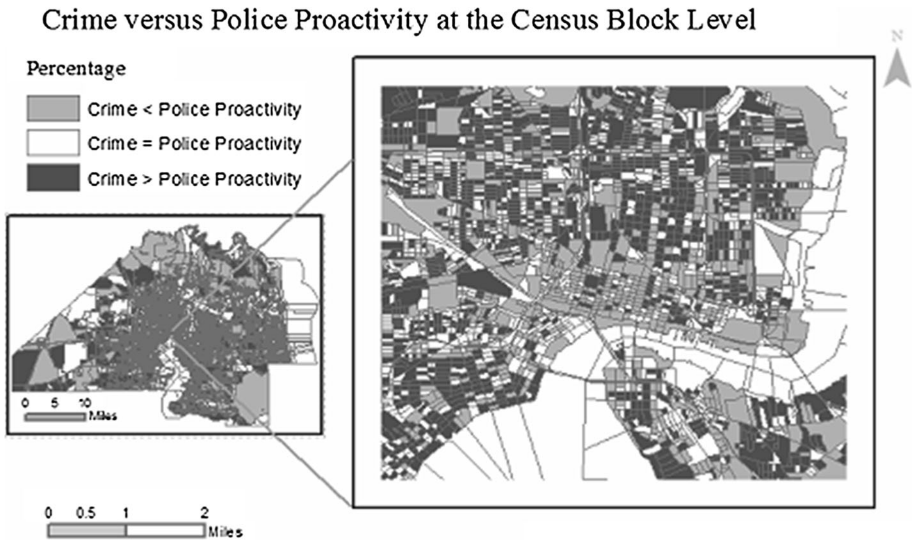


Fig. 4 SPPT map at the census block level

Most strikingly, much higher levels of variability are observed at the census-block and the street-segment levels. Illustrating this is a map constructed at the census-block level that presents the local relationship between crime and proactivity in the central area of Jacksonville (see Fig. 4). Census blocks next to each other might have contrasting patterns of proactive or reactive resource distribution. Some blocks have proportionally higher citizen crime and disorder calls (black areas), some have more proactive activity (gray areas), and some are more balanced (white areas). This high variability at the census-block level (as well as the street-segment level) suggests there may be a great deal of street-by-street variability in proactive police resources relative to the amount of crime. In other words, although this cannot be confirmed here, the JSO patrol officers appear to be targeting their self-initiated activities at more micro-units. This variability may also reflect spatial heterogeneity of crime itself at the micro level, as suggested by Weisburd et al. (2004). Overall, our maps present spatial patterns between proactivity and crime that are generally similar across spatial units, but important variations are disguised when larger spatial units are used.

It is important to note that even though we expect places with more crime to receive more proactive police activities, we do not expect such a relationship to be consistently proportional, especially at the micro level. It may be unrealistic and unnecessary to proactively dispatch patrol officers to micro places across the city based on a simple numerical calculation of citizen calls, and police can be place-focused without meeting a given proportionality. Moreover, despite the stability of crime at places over the long run (see Weisburd et al. 2004), the number of citizen calls occurring at micro places can change over shorter periods of time, leading to changes in the distribution of proactive activity. In other words, observed variability does not imply a non-place-based patrolling strategy.

Further, even in places that share the same color-coded classification, the dynamic between police proactivity and crime is not necessarily the same. There are at least two possible circumstances in which police proactivity is proportionately greater than crime.

Table 3 Percentages of S index controlling for crime levels

% place on scale of crime	Model 1			Model 2			Ave. crime	% of total proactivity	% of total crime
	Negative % (proactivity)	Zero %	Positive % (crime)	Negative % (observed)	Zero %	Positive % (predicted)			
50	12.7	76.9	10.5	14.3	81.1	4.6	0.4	4.3	1.1
50–75	17.7	14	68.4	21.4	16.4	62.2	7.3	10.7	11.6
75–90	15.6	10.1	74.3	15	8.7	76.2	21.0	17.2	20
90–95	26.6	7.9	65.5	21.9	9	69.1	47.0	13.8	14.9
95–100	36.2	5.9	57.9	31.3	5.9	62.8	164.6	54.1	52.3

First, police conducted a significantly higher proportion of proactive work in the central part of the city where crime is most concentrated. At the same time, police also conducted greater levels of proactivity at some of the peripheral areas that are relatively free of crime. Police might conduct traffic-related proactive efforts in these outer areas, which have numerous major roadways. However, an additional examination of police proactivity in some of these outer areas suggests that service work such as "checking individual or property" seems to account for the majority of police proactive work in the outer areas where proactivity is proportionately greater than crime. This phenomenon could reflect an attempt by the police agency to be more equitable either in their resource allocation or in the more general spatial distribution of beat patrol in the standard model.

The local S-Index categorizes the relationship between crime and proactivity into one of the three groups (−1, 0, and 1). However, because it uses proportions of each category to their totals, it does not feature variations of crime levels. For example, we cannot infer from Fig. 4 the relationship between crime and proactivity in places with high or low levels of crime. For example, a place with 5 % proactivity and 5 % crime compared to their respective totals has an S-Index of "0." but we don't know if this non-significant difference is in a very high or very low crime location. To compensate, we controlled for the amount of crime and calculated the percentage of the three S-Index values at places with fixed crime levels. As shown in the model 1 of Table 3, census blocks are ranked by crime level and divided into five unequal-sized groups where the average amount of crime ranges from 0.4 to 164.6. The majority of the bottom 50 % of the census blocks are assigned a "0," suggesting a similar percentage of crime and proactivity, which is not surprising given that they are mostly crime-free places. The percentage of census blocks with higher crime ("+1") is consistently higher than the percentage of those with more proactivity ("−1"). However, as crime at places increases, the percentage of places with higher proactivity increases as well. At the top 5 % of census blocks with the highest crime, 36.2 % of them received proportionately higher proactivity, compared to 15.6 % of places between the 75th to 90th percentiles on crime level.[7] It is clear that the hottest census blocks received additional proactive resources by patrol officers in 2013, although crime still proportionately outnumbers proactivity in a substantial proportion of places.

[7] It is important to note that, however, the absolute difference between crime and proactive calls at places may not be large. For example, at the hundred block level, in 90 % of places, the absolute difference between proactivity and crime is within 17. Only in 0.5 % of places, the absolute difference between two measures exceed 100. A handful of places experienced over a thousand more proactive calls, whereas places with more crime calls experienced more modest contrast with the maximum difference being 477. The average difference is 5.9 when crime outnumbers proactivity and 5.1 in the opposite direction.

This is again confirmed by the percentage of total proactive calls and the percentage of total crime in the last two columns of Table 3. Overall the percentages of proactivity in places with a range of crime levels do not differ largely from those of crime, but proactive police work concentrates substantially as crime goes up. For the 5 % of places that have the most crime, the police concentrated over half of their police-initiated activity.

As suggested by one of the reviewers, the null hypothesis for the SPPT analysis indicates that there is no spatial relationship between crime and proactivity measures, which may be too generous since we might expect places with high crime to also have more proactive activity. To address this issue, we performed a more stringent test by comparing the observed proactivity at places with those predicted by crime. Specifically, a regression function is fitted to proactivity based on crime at the census block level, the result of which is used to generate predicted values of proactive work.[8] Next, the SPPT analysis is conducted once again where the predicted proactivity serves as the base point and the observed proactivity as the test point. Results after controlling for levels of crime are reported in model 2 of Table 3.

Overall, police conducted 31,840 (13.5 %) more proactive acts above what is predicted by crime. Such preponderance of actual proactive work, however, is not reflected in the percentage of places with higher proportions of observed proactivity. As suggested by model 2 in Table 3, the majority of places with middle to high crime problems experienced lower proportions of actual proactive police acts than predicted by crime. However, similar to model 1, the likelihood for a place to experience higher proportions of actual versus predicted proactive work becomes greater as crime goes up.

Thus, the results of the SPPT analysis show that police in Jacksonville seem to know where crime occurs, and that they concentrated proactive resources at places with the most crime. Although crime or predicted proactivity still out-proportions actual proactive work at middle to high crime places, a closer investigation of the data revealed that it is not a lack of overall proactive work but potentially varied organizational or officer factors that may lead to the unbalanced distribution of proactive police actions. Indeed, the amount of observed proactive work exceeds the volume of either crime or expected proactivity. Further, when observed proactivity exceeds crime or expected proactivity at places, this difference is much more prominent than the difference in the opposite direction. At the top 5 % of census blocks with most concentrated crime, the average difference is around 55 when the expected proactivity exceeds the observed with the maximum difference being 356. However, this difference increases to 132 when the observed exceeds the predicted levels of proactivity, with the maximum difference being 1897. Thus we observed a greater number of places with higher proportions of crime or expected proactivity, even though the actual levels of proactive work is greater than crime. While we cannot tell from this analysis the effects of the high levels of proactivity on crime at these places, this analysis does indicate that given the amount of proactive effort devoted by Jacksonville officers relative to crime, we can see this agency shows a commitment to being proactive and place-based.

Part II: Do Police Spend More Time at Places with Higher Levels of Crime?

Table 1 shows that, on average, police are spending 40 min on each proactive activity, though this varies depending on the type of activity involved. However, the question we are concerned about is whether they spend more time being proactive in places with higher

[8] A linear function is assumed between crime and the factual proactive work.

amounts of crime. To examine this question, we employ OLS regression models using four different spatial units—the census tract, the block group, the census block, and the hundred block.

Before doing this, we test one important assumption of the OLS model—linearity, which as we previously mentioned might not hold up in our analysis. For example, at places that are exceptionally high in crime, officers might have less time to be proactive, because they are answering many more calls for service. This might not be the case at places with medium to high levels of crime, where there may be more opportunities for officers to be proactive. Officers might also misidentify hot spots, as suggested by Ratcliffe and McCullagh (2001), and thus be conducting proactivity in low-crime places. Another possibility is that officer proactivity has led to some places having low levels of crime. For whatever reason, if such curvilinearity exists, OLS regression models become much less reliable.

To help illustrate this possibility, we use scatterplots representing the relationship between the percentage of crime and the percentage of proactive activities at each location (Fig. 5a), and also crime and the total amount of time on proactive activities (Fig. 5b) for each hundred block in Jacksonville. There is generally a positive relationship between crime and police proactivity and crime and proactive time at these places. However, some notable outliers of hundred blocks have low crime but high levels of police proactivity (and time spent on those activities).

A closer examination of these outliers indicated that many of them were places in which high levels of proactive time might be expected (e.g., Traffic operation center, highways, public parks, and shopping centers). For our analysis here, and given the uncertainty of the cause of these outliers, we removed them from our analysis. Figure 5c, d replot the relationship between crime percentage and police proactivity percentage, and crime and proactive time at hundred blocks after deleting outliers from the sample. The solid line suggests the "fitted values," or the values predicted by the regression model, and the dashed line shows the local relationship between variables of interest.[9] As seen on the graph, there is a slightly upward and increasing curvilinear relationship between crime and proactive work of patrol officers (different from the increasing–decreasing curvilinear relationship proposed at the outset). More specifically, as crime goes up, the amount of proactive activities and also proactive time police allocated at places seems to grow larger with increasing speed, suggesting that patrol officers in Jacksonville are for the most part trying to allocate disproportionately more proactive resources at places with higher levels of crime. In particular, the local relationship deviates upward from the regression line when the amount of crime is larger than roughly 200 crimes per year at the hundred-block level. This may explain why the SPPT returned such low indices of similarity even though patrol officers seem to be doing place-based proactive work. It also reflects the qualitative knowledge we have of a hot spot policing orientation in Jacksonville.

[9] The local relationship is graphed by performing the *lowess* function in STATA. *Lowess* carries out a locally weighted regression of the dependent variable on the independent variable. It creates a new variable that, for each y_i, contains the corresponding smoothed value. The smoothed values are obtained by running a regression of y on x using only the data (x_i, y_i) and a few of the data near this point. The regression is also weighted so that the central point gets the highest weight and points that are farther away receive less weight. The subset used in calculating y is indices $i_- = \max(1, i - k)$ through $i_+ = \min(i + k, N)$, where $k = [(N^* \text{bwidth} - 0.5)/2]$. The weights for each observation are tricube, $w_j = \left\{1 - \left(\frac{|x_j - x_i|}{\Delta}\right)^3\right\}^3$ where $\Delta = 1.0001 \max(x_{i+} - x_i, x_i - x_{i-})$. The smoothed value is then the weighted regression prediction of x_i. For more information, see http://www.stata.com/manuals13/rlowess.pdf.

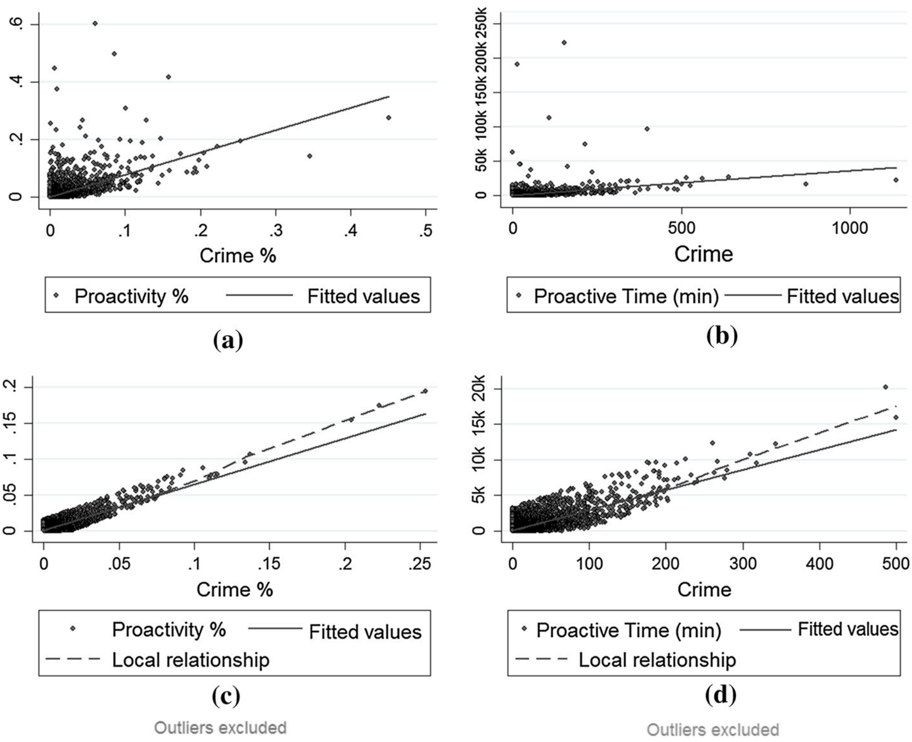


Fig. 5 Twoway graph between **a** the % of crime and the % of proactive events, **b** crime and the amount of proactive time, **c** crime % and proactive events % excluding outliers, and **d** crime and proactive time excluding outliers, at each hundred block

The upward curvilinearity between crime and proactive measure is confirmed in the regression models. Table 4 shows the results of the regression analysis with (model 1) and without (model 2) the squared term of crime when the outliers are excluded. The monomial and binomial terms of proactivity are significant across spatial units and models, supporting observations in the two-way graphs above. First, the amount of proactive events or proactive time spent at places are positively correlated with crime counts.[10] Further, the amount of proactive events associated with each crime and disorder call is higher at places with high enough crime. As illustrated in the two way graphs, such upward tendency becomes observable at hundred blocks with more than 200 crime and disorder calls per year. Considering the small scale of the curvilinearity as shown by the microscopic coefficient value of the squared term and the fact that the vast majority of places have no or small levels of crime, the OLS regression models are still able to provide useful information despite the curvilinearity observed.

Overall, the coefficient values remain high and stable across different levels of spatial scale, indicating that patrol officers in Jacksonville are not only proactive, but also allocate their time accordingly even at small geographic scale. For example, at the hundred-block level, each crime call at places is linked to 0.7 of a proactive call or over 28 more minutes

[10] Regression models were also performed using the percentage of crime and the percentage of proactive events at each location. Results are similar to the ones presented in that both the monomial and binomial terms of the percentage of crime are significant across spatial units.

Table 4 OLS regression models

	Model 1						Model 2					
	Proactivity			Proactive time (min)			Proactivity			Proactive time (min)		
	Coef.	N	R^2	Coef.	N	R^2	Coef.	N	R^2	Coef.	N	R^2
Census tract												
Crime	0.89***	165	0.78	36.09***	170	0.76	0.56***	165	0.80	26.64***	170	0.77
$Crime^2$							0.00***			0.00*		
Block group												
Crime	0.96***	473	0.75	37.16***	483	0.69	0.59***	465	0.78	22.53***	475	0.71
$Crime^2$							0.00***			0.01***		
Census block												
Crime	0.91***	14,601	0.82	35.34***	14,793	0.76	0.79***	14,593	0.81	30.98***	14,796	0.77
$Crime^2$							0.00***			0.01***		
Hundred block												
Crime	0.70***	50,111	0.67	28.50***	50,600	0.57	0.60***	50,080	0.66	25.02***	50,591	0.57
$Crime^2$							0.00***			0.03***		

* Suggests significance at 0.05 level, ** denotes significance at 0.01 level, and *** denotes significance at 0.001 level

of proactive time police spend at that place, suggesting a moderately high level of proactive efforts at the micro unit by patrol officers in Jacksonville. The amount of variance explained goes down as the spatial unit goes down (except at the census-block level), which is expected, as there are more cases and higher levels of variance to explain at lower spatial scales. Moreover, considering also the upward curvilinearity observed, the figure will grow even higher as crime at places goes up, making the patrol strategy in Jacksonville a highly proactive, place-based, and geographically micro-scaled one.[11]

Discussion

Ever since Sherman and Weisburd (1995) found a positive impact from increased police presence on crime and disorder at crime hot spots, many studies have established solid evidence that police can be effective by allocating their resources in proactive and place-based ways. Efforts have then been made to not only understand what works, but also to understand whether practitioners are employing what works and how research evidence can be translated into practice (Lum et al. 2012; Lum and Nagin 2016; Sherman et al. 2014). However, agencies face a number of challenges with these efforts to become more place-based and proactive. One important challenge that has received little attention in the literature has been the issue of performance measurement. Specifically, how can we measure whether officers conduct more proactive work and spend more time on proactive work at places with high levels of crime?

In this paper we offer one approach to measuring a law enforcement agency's proactivity, and discovered that officers in the Jacksonville Sheriff's Office, at least during the time this study was conducted, showed a commitment to place-based and proactive, self-initiated activities. For the categories of events we measured, it appears they spend a large proportion of their resources (over half) conducting proactive work, and concentrate their proactive resources in the most crime-ridden areas (see Table 3). Such patterns hold when either using crime or the expected levels of proactive work based on crime as the reference group. Even though the intensive concentration of proactive activity did not seem to extend to every place with high crime, those that did received more proactivity were targeted intensively and overall places with the most serious problems were prioritized in proactive police work. On average, for every crime call received at a hundred block, the police generated around 0.7 extra proactive activities and spent more than 28 extra minutes there

[11] A concern related to polynomial models may be the potential for large error resulting from the high covariance or dependency between parameters. To minimize the math error, we centered the model by subtracting the mean from the independent variable and performed the regression analyses again (a technique used by Bradley and Srivastava 1979). Results of the centered model remained unchanged for *p* value and R square, while increases were seen for coefficient values. Each crime is now related to slightly higher proactivity or proactive time police allocated at places in the centered model, making it safe and reliable to conclude that JSO is highly proactive and place-based in allocating its patrol resources. We also test spatial autocorrelation, a general issue in spatial-oriented analysis that describes the degree of dependency between the spatial location and the variable measured at that location (Chainey and Ratcliffe 2005; Ratcliffe 2010). In plain terms, spatial autocorrelation suggests that places near each other are more alike (positive correlation) or less alike (negative correlation). Failing to account for spatial autocorrelation in the dependent variable will tend to underestimate the real variance in the data, increasing the likelihood of a Type I statistical error (Ward and Gleditsch 2008, as cited in Ratcliffe 2010). There are many ways to control for spatial dependency. In this article, we test it with Lagrange Multiplier test and control for it by running a spatial error model. Even though significant spatial dependency indicators are observed in some of the models, results for our variables of interest do not change much.

carrying it out. Such figures hold stable across spatial scales, suggesting the commitment of police in Jacksonville toward concentrating their activities in crime hot spots. There are, of course, outliers where the amount of proactivity or proactive time allocated to places differs significantly from the amount of crime at those places. But our findings are consistent with the vast majority of places, indicating JSO has a proactive deployment strategy generally. This analysis also shows an analytic approach to determining the proactive performance of the agency, an important measure in an era when police agencies and researchers are calling for more proactivity at crime hot spots.

Like other studies using observational data, our study suffers from potential endogeneity problems, especially since the relationship between crime and proactivity at places is likely to be bidirectional. For example, suppose crime at places increases. Police may respond with intensive patrol or crackdown at those places, leading to increased levels of proactivity and time there, which will likely, in turn, impact the local crime levels (Nagin et al. 2015). While our study focuses on the measurement of police proactivity in relation to crime, such measurement will be affected by the underlying causal mechanism between proactivity and crime, as they do not stay static. With the current dataset, we cannot detect the ongoing process and causal link between crime and proactivity at places. Longitudinal analysis and experimental tests of proactivity is needed for such purposes.

Important nuances in the definition of police proactivity also suggest caution when trying to understand police proactive work and its relationship to crime. For instance, even though we measure police proactivity as all events in the calls for service data that were initiated by police officers, different types of proactive work can result from different police processes. Some proactive work might arise from a long-term perspective on and analysis of long-standing historical and contextual problems of places (Hunt et al. 2014). However, police could also be assigning more proactive resources to places as a response to short-term crime spikes (which some might considered more reactive than proactive). Proactive policing may also be more amenable to outdoor events and crime, rather than crime that occurs inside homes and buildings. Thus, it may be more appropriate to compare police proactive work with outdoor crime, rather than indoor crime. Unfortunately, we are unable to distinguish such differences from our data. Even in a progressive agency that keeps track of officer proactivity, the reporting of this activity remains ambiguous.

Further, it is conceivable that responding to citizen calls in high crime areas could leave fewer resources for patrol officers to conduct proactive work. When that happens, places with more crime than proactive work might reflect a lack of available resources in those areas rather than that police are not being proactive. Assigning more officers to work proactively in high-crime places, and thus taking them away from low-crime areas, could be met with resistance from the police and citizens. Our results suggest that the Jacksonville police, while still prioritizing places that are most crime-ridden and thus have the greatest needs, also provided considerable amounts of proactive efforts in places with less crime. Officers may carry out different types of proactivity in places with high- or low-crime levels, and proactivity may be a more general goal of the department in providing for general well-being, equity of resource allocation, or good citizen relations.

In addition to addressing these nuances, this study also raises questions about the cost-efficiency of police work. For example, the median[12] time patrol officers spent on a citizen call for service in Jacksonville was around 29 min in 2013. As suggested by Nagin et al. (2015), if a patrol officer spends 29 min proactively at a place, can he or she thereby

[12] We report the median value since the mean is distorted by crime calls—like homicide investigations—which may take up a great deal of allocated time.

prevent at least one crime call, thus saving time that would have been spent on a future call? This question is critical in that it points out the possibility of reducing crime through adjusting the existing amount of time police spend on proactivity (see also Koper 1995). If the answer is positive, police will reduce crime with no need for extra resources. More understanding is needed about how officers spend their time, what types of activities they are trained in and expected to carry out when not answering calls for service, and what types of information, technologies, skill sets, knowledge, and other tools they need to be proactive.

The mechanisms that govern the relationship between crime and police proactivity are complicated. However, this study contributes to an important question—should police proactivity be at least proportional to the amount of crime or crime opportunities at places? Given evaluation research knowledge about the effectiveness of proactive approaches in preventing crime, we think it should be. Our paper provides some ideas on how such proportionality might be quantified, measured and judged.

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