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Using Terror Alert Levels to Estimate the Effect of Police on Crime

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Abstract: Changes in the terror alert level set by the Department of Homeland Security provide a shock to police presence in Washington, D.C. Using daily crime data during the period the terror alert system has been in place, we show that crime drops significantly, both statistically and economically in Washington during high-alert periods. The drop in crime is especially large in the National Mall. This provides strong evidence of the causal effect of police on crime and suggests a research strategy that can be used in other cities.

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Introduction

Do police deter crime? A majority of studies surveyed by Cameron (1988) found either no relationship or that increases in police are associated with increases in crime. Most economists are suspicious of these results. It is no surprise to find that places with an inordinate amount of crime tend to employ a large police force. Nor is it unreasonable to suspect that jurisdictions increase the size of their police forces when they witness or expect an increase in crime. Thus, neither cross-sectional nor time-series analyses can credibly identify a causal effect of police on crime. But crime and crime fighting cost Americans hundreds of billion of dollars every year. Expenditures on police alone, for example, are over 65 billion dollars a year.[1] The enormous expenditure on policing makes breaking the endogeneity circle more than a mere academic puzzle. Isolating a causal relationship between increases in police and reductions in crime has large policy consequences.[2]

Terror Alerts as Shocks to Police Presence

In a seminal paper, Steven Levitt (1997) showed how the circle could be broken by identifying variations in police presence that were *not* caused by variations in crime.[3] Levitt found that police presence increased in mayoral and gubernatorial election years but not in off-election years. Since crime is unlikely to be correlated with election timing, this identification strategy can, in principle, break the circle. However, this

[1] Justice Expenditure and Employment in the U.S. 1999 (Bureau of Justice Statistics).
[2] It is interesting to note that combining police ($65 billion), judicial ($35 billion) and correction expenditures ($49 billion) total direct spending on criminal justice is $149 billion - more than a quarter of that spent on elementary and secondary schooling ($433 billion as of 2001). Yet there are many more papers on the return to education than on the return to policing.
[3] Marvell and Moody (1996), Corman and Mocan (2000) and Levitt (2002) are among other notable attempts to break the endogeneity circle.

strategy proved to be problematic in practice. Variations in police brought on by electoral cycles are not large and variations in other factors impede precise estimation. Although Levitt (1997) initially did estimate a significant deterrent effect, McCrary (2002) later showed that a programming error made Levitt's results appear more precise than justified. McCrary concluded, "In the absence of stronger research designs, or perhaps heroic data collection, a precise estimate of the causal effect of police on crime will remain at large."[4]

Inspired by Levitt's approach, we claim that a stronger research design than used in the past and a new data source let us better estimate the causal effect of police on crime. On March 11, 2002, the Office of Homeland Security introduced the *Homeland Security Advisory System* (HSAS) to inform the public and other government agencies about the risk of terrorist attacks. During high-alert times the police increase their presence on the streets of Washington, D.C. We use the high alert periods to break the circle of endogeneity to estimate the effect of police on crime.

In addition to a stronger research design than used in the past we also improve on the data. Most previous studies use annual data. Annual data are subject to an inherent tradeoff – a longer time-series improves the precision of estimates but increases the possibility of omitted variable bias. Panel data reduce the need for a long time series but raise the problem of endogeneity and omitted variable bias in the cross-sectional component.[5] We use daily crime data from a single city, Washington, DC, for our

[4] Levitt (2002) concedes the errors McCrary (2002) identifies. However, Levitt (2002) provides estimates using the number of municipal workers and firefighters as instruments to show that there is a statistically significant negative effect of police on crime.

[5] Glaeser, Sacerdote, and Scheinkman (1996) write that "the most intriguing aspect of crime is its astounding high variance across time and space." They go on to note that economic and social conditions per se can explain only a fraction of this variance suggesting omitted variable bias could easily skew results.

analysis. Daily data are less subject to endogeneity problems from crime to police. Also, our focus on a single city reduces omitted variable bias in the cross sectional component.

Data and Research Design

We use daily police reports of crime from the Metropolitan Police Department of the District of Columbia (Washington, D.C). These are the same data that the Police Department uses for its internal decisions and statistical analysis.[6] Our data cover the time period since the alert system began, March 12, 2002 to July 30, 2003. During these 506 days there were 55,882 crimes, or an average of 110 per day. Table 1 provides further details on the number of crimes during this period by crime category.

The HSAS alert system is broken into 5 color-coded threat conditions: Low (Green), Guarded (Blue), Elevated (Yellow), High (Orange) and Severe (Red). Since its inception, the HSAS has never fallen below Elevated, but, on four occasions during our time period, it has risen to High, the second highest level. The alert rose to high on the following dates: September 10-14, 2002; February 10-27, 2003; March 17-April 16, 2003; and May 20-30, 2003.

It is important to understand that the primary purpose of the HSAS is *not* to advise the public. The primary purpose is to inform and coordinate the anti-terrorism efforts of all federal agencies. The HSAS alert system is binding on all federal agencies (except the military), which must conform their anti-terrorism efforts to the HSAS threat

[6] The MPD's internal crime data may vary somewhat from official index totals as reported to the FBI for a variety of reasons including late reporting and reclassification of some offenses. The MPD requires that the following disclaimer be made: "These data reflect preliminary crime reports made by individual police districts to the MPD's Central Crime Analysis Unit. These data DO NOT reflect official index crime totals as reported to the FBI's Uniform Crime Reporting Program. These data are subject to change for a variety of reasons, including late reporting, reclassification of some offenses, and the discovery that some offenses were unfounded."

level. High alert status indicates a high risk of terrorist attack. During a high-risk period government agencies take actions such as "coordinating necessary security efforts with Federal, State and local law enforcement . . . taking additional precautions at public events . . . preparing to execute contingency procedures . . . restricting threatened facility access to essential personnel only."[7]

Although the HSAS is not binding on state and local law enforcement agencies, they are strongly encouraged to monitor the HSAS and take appropriate actions. For obvious reasons, the police in Washington DC are acutely aware of the threat level. During a high-alert period, the Washington police department increases the number of patrols, increases the length of shifts in order to put more police on the street, and activates a Joint Operations Command Center which is run by the DC Police but also includes federal, regional and other local officials. In addition, to increasing its physical presence, the police department increases its virtual street presence by activating a closed circuit camera system that covers sensitive areas of the National Mall. The camera system is not permanent; it is only activated during heightened terror alert periods or during major events such as Presidential inaugurations.[8]

[7] See Homeland Security Presidential Directive-3 at http://www.whitehouse.gov/news/releases/2002/03/20020312-5.html, accessed September 29, 2003.

[8] Understandably, the DC Police are reluctant to discuss in any detail the actions that they take during a heightened terror alert. The increased patrols and activation of the closed circuit television system is discussed in an official news release from February 27, 2003 (see http://mpdc.dc.gov/news/news.shtm). Unofficially, we were told that during heightened alert periods the police department switches from three 8-hour shifts a day to two 12-hour shifts, thus increasing the effective police presence by 50% (with 3 shifts of x police there are 3x police on the street per day, with two shifts there are 2y, assuming that 2y=3x (the same number of police are allocated over the day) then y=3/2x, an increase of 0.5) . Despite several requests, however, the DC Police would neither confirm nor deny this exact procedure.

Results

The results from our most basic regression are presented in Table 2 where we regress daily D.C. crime totals against the terror alert level (1=High, 0= Elevated) and a day of the week indicator. The coefficient on the alert level is statistically significant at the 5 percent level and indicates that on alert days total crimes drop by an average of 7 crimes *per day* or approximately 6.6 percent. Also potentially of interest, we find that crime is much higher on Fridays (more specifically Friday nights[9]) than on other days.

We hypothesize that crime falls on high-alert days in Washington D.C. because of greater police presence on the streets. An alternative hypothesis is that tourism is reduced on high-alert days and, as a result, there are fewer potential victims, leading to fewer crimes.[10] We are skeptical of the latter explanation on theoretical grounds because holding all else equal, *daily* crime is unlikely to vary significantly based on the number of *daily* visitors. The vast majority of visitors to Washington D.C. are never the victim of a crime. Since there are far more visitors than crimes it seems unlikely that the number of visitors constrains the number of crimes. More plausibly, the number of crimes is constrained by the number of criminals, which can be considered fixed on a daily basis.[11]

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[9] Our raw data allow us to examine the time of day that each crime occurred.

[10] The premise of the argument is dubious. We spoke with people at the The Washington DC Convention and Tourism Corporation (they monitor hotel occupancy rates), with people in the hotel industry as well as with the Washington police and the statistician for the DC Metro system and they all said that they had not noticed any reduction in tourism during high-alert periods.

[11] To illustrate consider the "gazelle-lion" model of crime. A large group of gazelles makes a daily trek to a watering hole. On average there are say 1,000 gazelles in the group but on any given day the group might be anywhere between say 800 or 1,200. The number of lions is constrained in the long run by the average number of gazelles but on any given day the probability that a lion catches a gazelle is fixed (it is no more difficult to catch a gazelle when the herd is 800 than when the herd is 1,200). Gazelles, of course, prefer to travel in large groups to lower their individual chances of being victimized but the number of gazelles eaten daily depends only on the number of lions and not on the number of gazelles.

To test whether fewer visitors could explain our results we obtained daily data on public transportation (Metro) ridership.[12] In column ii of Table 2 we verify that high-alert levels are not being confounded with tourism levels by including logged mid-day Metro ridership directly in the regression. The coefficient on the Alert level is slightly smaller at -6.2 crimes per day. Interestingly, we find that increased Metro ridership is correlated with an increase in crime. However, as the lion-gazelle model (see footnote 11) predicts, the increase is very small – a 10% increase in Metro ridership increases the number of crimes by only 1.7 per day on average. Thus, given that mid-day Metro ridership is a good proxy for tourism, changes in the number of tourists cannot explain the systematic change in crime that we estimate.[13] We offer another test of the tourism thesis below when we examine what happens to burglaries (a non-tourist based crime) during high-alert periods.

While suggestive of the effect of police on crime, our data provide more variation to exploit. Washington is split into 7 police districts. Each distinct might have its own peculiar crime pattern because of differences in geography, population density, income and so forth. Table 3, for example, indicates that some districts have twice as many crimes per day as other districts. To control for these differences in our regressions we include district fixed effects. More important, we make use of the fact that the White House, Congress, the Smithsonian and many other prominent government agencies and public areas of Washington are located in District 1, the "National Mall" area. We hypothesize that during a terror alert most of the increased police attention will be

[12] We also found data on monthly hotel occupancy rates, these actually increased during terror alert days although the increase was small and not statistically significant.
[13] Note that, generally speaking, midday ridership will consist mostly of tourists, rather than commuters who ride Metro during the rush hour periods.

devoted to District 1. As noted above, the police department can quickly increase its street presence through greater use of overtime, putting more officers on the streets instead of behind desks, and using the CCTV system. It is also possible that the Police Department diverts resources from other districts to the National Mall. The DC Police, however, have stated that official policy is that no regular patrols will be reduced during high alert periods.[14] If police presence were decreased in other districts we would expect to see higher levels of crime in other districts during high-alert periods. The analysis below, however, suggests no such effect.

The regression with district fixed effects is in Table 4. During high-alert levels crime in the National Mall area falls by 2.62 crimes per day. Crime also falls in the other districts, by 0.571 crimes per day but this effect is not statistically significant. Recall that on an average day there are 17.1 crimes on the National Mall, implying a decline during high alert days of approximately 15%, more than twice as large as found for the city as a whole. Stated differently, almost one half (43.6%) of the total crime drop during high-alert periods is concentrated in district 1, the National Mall area.[15]

We have argued that it is plausible that *most* of the increased police attention falls on District 1 because of the presence in that district of the White House, Congress, Supreme Court and so forth. It is revealing to take this argument one step further and assume that all of the increased protection falls on district 1. In this case, the difference

[14] See official news release from February 27, 2003 (http://mpdc.dc.gov/news/news.shtm).

[15] Allowing each district to have its own High Alert coefficient produces similar results. District 1 crime drops significantly during high alert periods (with a coefficient of -2.3, almost the same as earlier), while crime in the other districts falls slightly or not at all. The one exception is District 3 crime, which also experiences a statistically significant crime decrease although the decrease is smaller than in District 1 both absolutely and in percentage terms. District 3 borders District 1 and is very close to the White House, so it likely receives additional protection during high alert days. We also find similar results allowing each district to have its own day of week effects. Due to limited data, it's difficult in some of these specifications to estimate standard errors.

between the High Alert*District One and the High Alert*Other Districts coefficients is a difference-in-difference estimator that controls for all common factors between the districts. If bad weather, for example, causes decreases in crime, a coincidental correlation with high-alert timing could confound our results. The difference-in-difference estimator controls for any factors such as weather, tourism, or other events that affect the districts similarly. Even after controlling for all such factors and recognizing that our assumption is too strong we still find that cime falls in district 1 during high-alert periods by some 2 crimes per day or more than 12 percent.

Crime Specific Regressions

In Table 5 we examine crime specific regressions. For completeness we examine each of the crime categories but we caution that the daily number of Arsons, Homicides, and Sexual Abuse cases are low relative to the other categories. We find statistically significant coefficients for the High Alert*District 1 interactions, and the coefficient is negative for all offense categories except for thefts, robberies (theft accompanied by a threat of force) and homicides. Homicide is likely one of the crimes that is least deterrable by putting police on the streets (it may be deterrable on other margins) so the lack of a negative coefficient is not surprising – because of the low incident rate it would be unwise to draw strong conclusions from the positive coefficient. The positive coefficients on robberies and thefts are more surprising although the percentage changes they represent, 6 percent for robberies and 1 percent for thefts, suggest that the effect is not very large. For the remaining categories, we estimate that Assaults with a Deadly Weapon (ADW) drop by 9 percent in District 1 on high alert days, Burglaries drop by 15 percent, Automobile Thefts decline by 15 percent, and Thefts from Automobiles drop by 40 percent.[16]

The large declines in crime among automobile thefts and thefts from automobiles supports the idea that increased police presence is the driving force in reducing crime during high alert periods because these are "street" crimes. Temporary increases in street police and closed circuit cameras are unlikely to deter crimes such as homicide that often occur in homes among people who know one another but are much more likely to deter street crimes such as automobile theft.[17]

The negative and statistically significant coefficient on Burglaries is important because burglaries are *not* a crime against tourists. If the declines in crime that we find during high-alert periods were due to reductions in tourism rather than increases in police presence we would not expect to see a decrease in burglaries.[18]

Conclusion

Given the importance of police protection in budgetary terms and the welfare effects of crime, the lack of credible causal estimates of the effect of police on crime is troublesome. Although Levitt (1997) laid out a useful framework for isolating the causal effect of police on crime, limited variation in his primary instrument and data ambiguities limit the policy value of his estimates, as shown by McCrary (2002) and Levitt (2002).

[16] The low number of daily observations for Arson, Homicide and Sexual Abuse cases suggests that a negative binomial model might be appropriate in those cases. Qualitative results, available upon request, are similar to those reported here.

[17] On the location of homicides versus other crimes see Bureau of Justice Statistics (2003).

[18] Our coefficients on log(mid-day ridership) are potentially interesting as well. All the statistically significant coefficients are positive but small. It might seem surprising that we estimate a positive coefficient in the burglary regression given our observation above that burglaries are unrelated to tourism. However, it may well be the case that our ridership variable is picking up weather effects. Note also that the effect is miniscule, a 1% increase in mid-day ridership increases crime by .01* the respective Beta coefficient.

Taking a similar approach but focusing on the easily identifiable and clearly exogenous shock provided by changes in the terror alert level, we provide the first analysis of daily crime data to evaluate the causal effect of police on crime for the city of Washington, D.C. Using a variety of specifications, we show that an increase in police presence of about 50 percent leads to a statistically and economically significant decrease in crime on the order of 16 percent. We provide analyses that suggest that this decrease is not an artifact of changing tourism patterns induced by changes in the terror alert level.

While our research provides a credible estimate of the causal effect of police on crime, more research is needed to determine whether this effect and its magnitude can be generalized to other cities, or whether it is peculiar to the Washington D.C. area. In principle, our design, which uses terror alert changes as exogenous shocks to police presence and daily crime data, can be implemented in analyses of the crime patterns in other metropolitan areas.

References

Bureau of Justice Statistics. 2003. Criminal Victimization. 2002. NCJ 199994. http://www.ojp.usdoj.gov/bjs/pub/pdf/cv02.pdf

Cameron, Samuel. (1988). “The Economics of Crime Deterrence: A Survey of Theory and Evidence.” *Kyklos*, 41(2): 301-323.

Corman, Hope and Mocan, H. Naci. (2000). “A Time-Series Analysis of Crime, Deterrence, and Drug Abuse in New York City.” *American Economic Review*, 90(3): 584-604.

Glaeser, Edward L., Sacerdote, Bruce and Jose A. Scheinkman. 1996. Crime and Social Interactions. *Quarterly Journal of Economics* 111 (2): 507-548.

Levitt, Steven D. (1997). “Using Electoral Cycles in Police Hiring to Estimate the Effect of Police on Crime.” *American Economic Review*, 87(3): 270-290.

Levitt, Steven D. (2002). “Using Electoral Cycles in Police Hiring to Estimate the Effects of Police on Crime: Reply.” *American Economic Review*, 92(4): 1244-1250.

Marvell, Thomas and Moody, Carlisle. (1996). “Police Levels, Crime Rates, and Specification Problems.” *Criminology*, 34(4): 609-646.

McCrary, Justin. (2002). “Do Electoral Cycles in Police Hiring Really Help Us Estimate the Effect of Police on Crime? Comment.” *American Economic Review*, 92(4): 1236-1243.

Table 1
Crimes in Washington D.C. by Type
March 12, 2002 – July 30, 2003 (506 Days)

Offense Category	Total	Daily Average
Assault with a Deadly Weapon	5,682	11.2
Arson	129	0.3
Burglary	7,071	14.0
Homicide	368	0.7
Robbery	5,937	11.7
Sex Abuse	530	1.0
Stolen Auto	12,149	24.0
Theft	10,230	20.2
Theft from Auto	13,726	27.1
Total	55,882	110.4

Table 2		
Total Daily Crime Falls on High Alert Days		
(Robust Standard Errors in Parentheses)		
High Alert	-7.316*	-6.046*
	(2.877)	(2.537)
Log(Mid-Day Ridership)		17.341**
		(5.309)
Sunday	105.475	-88.413
	(2.116)	(59.571)
Monday	111.137	-90.896
	(1.879)	(62.018)
Tuesday	108.349	-95.375
	(1.663)	(62.428)
Wednesday	107.198	-96.453
	(1.869)	(62.539)
Thursday	107.336	-96.691
	(2.219)	(62.398)
Friday	125.234	-80.546
	(2.158)	(63.022)
Saturday	114.188	-85.335
	(2.061)	(61.066)
Observations	506	506
R^2	0.14	0.17

* Significantly different from 0 at the 5-percent level.
** Significantly different from 0 at the 1-percent level.
Note: The dependent variable is the daily total number of crimes (aggregated over type of crime and district where crime was committed) committed in Washington D.C. during the period March 12, 2002 to July 30, 2003.

Table 3
Crimes in Washington D.C. by District
March 12, 2002 – July 30, 2003 (506 Days)

District	Total	Daily Average
District 1 – "The Mall"	8,653	17.1
District 2	6,578	13.0
District 3	10,019	19.8
District 4	9,159	18.1
District 5	8,096	16.0
District 6	7,843	15.5
District 7	5,465	10.8

Table 4
Reduction in Crime on High Alert Days Is Concentrated on the Mall
(Robust Standard Errors in Parentheses)

	(i)
High Alert*District 1	-2.621**
	(0.044)
High Alert*Other Districts	-0.571
	(0.455)
Log(Mid-Day Ridership)	2.477**
	(0.364)
Constant	-11.058**
	(4.211)
Day of Week Dummies	Yes
District Fixed Effects	Yes
Observations	3,542
R^2	0.28

Note: The dependent variable is daily crime totals by district, except for the regression presented in column (iv), which uses daily crime totals by offense category and district. All standard errors are clustered by district.
* Significantly different from 0 at the 5-percent level.
** Significantly different from 0 at the 1-percent level.

Table 5
Offense Specific Crime Regressions
(Robust Standard Errors in Parentheses)

	ADW	Burglary	Robbery
High Alert*District 1	-0.120**	-0.288**	0.121**
	(0.009)	(0.010)	(0.011)
High Alert*Other Districts	-0.064	-0.169	0.014
	(0.068)	(0.104)	(0.095)
Log(Mid-Day Ridership)	0.508**	0.247*	0.026
	(0.074)	(0.097)	(0.161)
Mean in D1 During Period	1.330	1.951	1.881
D1 High Alert/Mean	-0.090	-0.148	0.064
R^2	0.17	0.10	0.14
	Stolen Auto	**Theft**	**Theft F/Auto**
High Alert*District 1	-0.430**	0.058**	-1.953**
	(0.028)	(0.015)	(0.032)
High Alert*Other Districts	0.091	0.065	-0.500
	(0.080)	(0.066)	(0.296)
Log(Mid-Day Ridership)	-0.133	1.128**	0.660*
	(0.213)	(0.235)	(0.236)
Mean in D1 During Period	2.810	4.006	4.919
D1 High Alert/Mean	-0.153	0.014	-0.397
R^2	0.30	0.42	0.25
	Arson	**Homicide**	**Sexual Abuse**
High Alert*District 1	-.015**	.020**	-.014**
	(.0009)	(.003)	(.002)
High Alert*Other Districts	-.008	-.004	-.006
	(.0044)	(.025)	(.0286)
Log(Mid-Day Ridership)	.027	.020	-.008
	(.016)	(.032)	(.019)
Mean in D1 During Period	.045	.061	.103
D1 High Alert/Mean	-0.333	0.328	-0.136
R^2	.01	.04	.02

Note: The dependent variable is the number of crimes committed by district in each of the offense categories during the period March 12, 2002 – July 30, 2003 (n = 3,542). Each specification includes day of the week dummies and district fixed effects, and all standard errors are clustered by district.
* Significantly different from 0 at the 5-percent level.
** Significantly different from 0 at the 1-percent level.