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

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Abstract: We argue that changes in the terror alert level set by the Department of Homeland Security provide a shock to police presence in the Mall area of 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 the Mall area relative to the other areas of Washington DC. 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 $146 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.[5] 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 endogenity and 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. We use daily crime data from a single city, Washington, DC, for our

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[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] We make no claims to heroism.

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 broken down by 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, 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 activate 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 presence on the street 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 1.5) . Despite several requests, however, the DC Police would neither confirm nor deny this exact procedure.

Results

The results from our most basic regression is 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.

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 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

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

high alert periods.[10] If police presence were decreased in other districts we would expect to see higher levels of crime in other districts during high-alert periods – we will test for such an effect.

Table 4 presents results of regressing crimes by district on an indicator variable set to 1 on high alert days in district one and another indicator variable set to 1 on high alert days in other districts. These specifications also include district and day of the week effects. We find that in District 1 the average number of crimes falls by a statistically and economically significant 2.8 crimes per day or a decline of 16.3 percent. Thus, we find significant evidence for a fall in crime with increased police attention. Other districts show a much smaller and statistically insignificant decline of 0.7 crimes per day so there is no evidence of substitution.[11] Standard errors are robust and clustered on district.

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. 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

[10] See official news release from February 27, 2003 (http://mpdc.dc.gov/news/news.shtm).
[11] This result is consistent with the official police policy not to divert resources away from the other districts to protect District 1 during high alert periods.

constrained by the number of criminals, which can be considered fixed on a daily basis.[12,13]

Moreover, it appears that the number of visitors does not fall greatly on high-alert days.[14] To test whether there are fewer visitors on high-alert days we obtained data on public transportation (Metro) ridership and hotel occupancy rates. Regressing mid-day Metro ridership on alert days and day of the week dummies we find a negative and statistically significant effect but the effect is small. We find that mid-day Metro ridership fell by 6,459 during alert days. The average daily mid-day ridership, however, is 114,000 so the decline is only 5.6%.[15] On hotel occupancy rates, which we could only obtain at a monthly rate, we find a small positive but statistically insignificant effect.[16]

In column ii we further 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 almost identical at -2.6 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 12) predicts, the increase is very small – a 10% increase in Metro ridership increases the number of crimes by only 0.2 per day on

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[12] 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.

[13] Note also that it is often said that crime rises when there are *fewer* victims – potential victims, for example, are told to "avoid walking alone."

[14] Both of the authors work in or near the Washington DC area and neither of us has taken any unusual actions during high-alert periods. We do not think that we are unusual in this regard.

[15] Even this decrease might over estimate the effect of alerts on the volume of people in D.C. since individuals may substitute away from public transportation toward driving in order to avoid the subways, which could be considered a terrorist target.

[16] We get qualitatively similar results if we use a fractional alert indicator, which measures the percentage of days in a month during which the terror alert is elevated.

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. 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.

It is also possible that other daily factors that we do not observe could influence crime and also be correlated with increases in the terror alert level. If bad weather, for example, causes decreases in crime, a coincidental correlation with high-alert timing could confound our results. We can control for all such unobserved factors by making use of the panel structure of our dataset. We have time series data on crimes for each of the seven districts. Any factor, such as the weather, that affects all districts can be controlled for with a "daily fixed effect." Note, that by a daily fixed effect we do not mean a set of day of the week dummy variables as we used earlier. In this specification, we use fixed effects for each of the 506 days in our sample. The daily fixed effect will control for day of the week effects as well as any factor such as the weather that is constant across districts.

The regression with daily fixed effects is in column iii of Table 4. The standard error on the High Alert*District 1 coefficient is much larger than before, which is not surprising given that all daily variation that is correlated across districts is now absorbed by the daily dummy. The coefficient, however, remains statistically significant and only slightly smaller than found earlier. During high-alert periods crimes are reduced by 2.05 incidents per day in District 1 relative to other districts on the same day.

We further generalize the regression by allowing each offense type in each district to have its own fixed effect. Thus there is a dummy variable for Arsons in District 1, another for Arsons in District 2 another for Burglary in District 1 and so forth. In addition, we continue to use the daily fixed effects as earlier. The coefficient on High Alert*District 1 is now interpreted as the daily reduction in crimes per district per offense category. A coefficient of -.227 thus indicates a fall in crime of 2.04 crimes per district per day – this is almost identical to the previous regression thus indicating that the increased flexibility introduced by giving crime/district interaction its own fixed effect is orthogonal to the affect of high-alert days on crime.[17]

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 robberies, thefts and homicides.[18] 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

[17] We find qualitatively similar results if we allow each district to have its own day of week effects.
[18] A robbery is a theft accompanied by a threat of force.

days, Burglaries drop by 15 percent, Automobile Thefts decline by 15 percent, and Thefts from Automobiles drop by 40 percent.[19]

The negative and statistically significant coefficient on Burglaries is particularly noteworthy since 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.[20]

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). 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

[19] 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.

[20] 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, since we cannot control for daily fixed effects in these models, 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.

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.

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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*
	(2.877)
Sunday	105.475
	(2.116)
Monday	111.137
	(1.879)
Tuesday	108.349
	(1.663)
Wednesday	107.198
	(1.869)
Thursday	107.336
	(2.219)
Friday	125.234
	(2.158)
Saturday	114.188
	(2.061)
Observations	506
R^2	0.14

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.
*Significantly different from 0 at the 5-percent level.

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)	(ii)	(iii)	(iv)
High Alert*District 1	-2.802**	-2.621**	-2.050**	-0.228**
	(0.033)	(0.044)	(0.479)	(0.050)
High Alert*Other Districts	-0.752	-0.571		
	(0.450)	(0.455)		
Log(Mid-Day Ridership)		2.477**		
		(0.364)		
Constant	10.037**	-11.058**	17.370**	1.359**
	(0.454)	(4.211)	(0.061)	(0.006)
Day of Week Dummies	Yes	Yes	No	No
Daily Fixed Effects	No	No	Yes	Yes
District Fixed Effects	Yes	Yes	Yes	No
District-Offense Fixed Effects	No	No	No	Yes
Observations	3,542	3,542	3,542	31,878
R^2	0.27	0.28	0.44	0.54

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.