Terror and the Costs of Crime*

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Abstract: This paper argues that terrorism, beyond its immediate impact on innocent victims, also raises the costs of crime, and therefore, imposes a negative externality on potential criminals. Terrorism raises the costs of crime through two channels: (i) by increasing the presence and activity of the police force, and (ii) causing more people to stay at home rather than going out for leisure activities. Our analysis exploits a panel of 120 fatal terror attacks and all reported crimes for 17 districts throughout Israel between 2000 and 2005. After controlling for the fixed-effect of each district and for district-specific time trends, we show that terror attacks reduce property crimes such as burglary, auto-theft, and thefts-from-cars. Terror also reduces assaults and aggravated assaults which occur in private homes, but increases incidents of trespassing and "disrupting the police." Taken as a whole, the results are consistent with a stronger deterrence effect produced by an increased police presence after a terror attack. A higher level of policing is likely to catch more people trespassing, and at the same time, reduce the number of property crimes. The decline in crimes committed in private houses is likely an indication that the tendency for individuals to stay home after a terror attack further increases the costs of crime.

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I. Introduction

In recent years, a burgeoning literature has emerged on estimating the consequences of terrorism on the economy. Abadie and Gardeazabal (2003) examined this issue in the context of Spain, while the case of Israel has been examined by Eckstein and Tsiddon (2004), Berrebi and Klor (2009), and Eldor and Melnick (2004). Recent research has also focused on how terror affects individual behavior. For example, Becker and Rubinstein (2007) show that individuals over-react to incidents of terrorism in a manner wildly disproportionate to the miniscule chances of being a victim in such an attack. Stecklov and Goldstein (2004) find that fatal traffic accident rates in Israel exhibit a steep rise shortly after terror attacks.

Yet, one dimension that has received little attention is whether terror affects crime rates. If terror attacks affect the level of crime or types of crimes that are committed, this suggests that there is an indirect mechanism, in addition to the direct loss of life and property damage, through which society is affected by terror. During the period between 2000 and 2005, Israelis experienced over 100 fatal terror attacks. Our paper is the first to study the temporal and spatial impact of terror on a wide range of crimes at the national level, using daily data on all crimes committed in Israel from 2000 to 2005. The large number of attacks, combined with data on every crime reported in Israel during the same period, provides a unique opportunity to study how crime levels respond to terror.

Our empirical analysis employs a daily panel of terror incidents and various categories of criminal activity for 17 subdistricts throughout Israel. The data contain information on the location and number of casualties from 120 terror attacks in Israel from October 2000 through December 2005. A "terror attack" in our analysis is defined as having at least one fatality, but we also test whether larger attacks (with five or more fatalities) produce stronger or weaker effects.

After controlling for the fixed-effect of each subdistrict and subdistrict-specific time trends, the results show that terror in Israel significantly reduces property crimes such as burglary, auto-theft, and thefts-from-cars. These reductions occur on the day of the attack and for up to five days afterwards. It should be noted that burglary and thefts-from-cars are the two most common types of crime, and auto-theft is the fourth most common (assault is number three). Terror does not seem to have a strong effect on sexual or violent crimes, although there does appear to be a reduction in assaults and aggravated assaults occurring in private homes. In addition, there is evidence that terror induces an increase in incidents of trespassing and disrupting the police.

The pattern of results across distinct types of crimes allows us to evaluate the relevance of various channels through which terror may affect crime. These channels are discussed in detail in the next section, but they generally fall into two broad categories: (1) those affecting the cost of committing crime, or (2) those influencing the propensity of criminals to commit crime. Terror affects the costs of crime primarily by the increased police presence on the streets after an attack (Levitt 1997; Di Tella and Schargrodsky 2004; Evans and Owens 2007). However, people also tend to stay home after an attack, and this raises the cost of committing crimes – particularly in private residences relative to public places (Cohen and Felson 1979; Cohen, Felson et al. 1980; Hipp, Bauer et al. 2004). Terror may also affect the propensity to commit crime in both directions. Terror may increase an individual's sense of social solidarity, which should reduce the motivation to commit crimes against fellow citizens (Cullen 1994; Landau 1997). However, if terror attacks increase social stress or risk-taking behavior, this could lead to higher levels of crime.

Overall, our results do not show that terror increases crimes levels. As such, our findings refute the argument that terror increases crime levels through increased social stress or risk-taking behavior. Instead, our results are consistent with terror raising the costs of crime -- through increased policing or changes in leisure activities after an attack. Both of these factors are likely to reduce property crimes, such as burglaries, in private homes. However, the reduction in assaults and aggravated assaults committed in private homes is most likely due to a change in leisure activities (staying at home more often), since the presence of more police on the streets is unlikely to strongly affect crimes committed in private homes. It is possible that an increasing sense of social solidarity contributed to the reduction in crimes committed in private homes, but this mechanism is inconsistent with the lack of any reduction in violent crimes committed in public places.

The reduction in property crime committed in public places is likely due to the increasing presence of police. Further evidence in support of the police size effect is provided by the increasing public incidents of trespassing and "disrupting the police" after a terror attack. A higher presence of police after an attack should reduce property crime, while at the same time increase the chances of catching someone trespassing. Also, more police on the streets should increase the number of interactions between citizens and police officers in public places, thus raising the probability that a "disruption of the police" occurs. The positive impact of terror on police activity is consistent with our analysis of the Israeli Labor Force Surveys (LFS) from 2000-2005, which shows that a local terror attack increases the probability that a police officer works overtime during the week of the attack. Taken as whole, the results strongly indicate that terrorists raise the costs of crime, and therefore, impose a negative externality on potential criminals.

No existing paper examines the systematic response of various types of crime to a sustained wave of terror. The most related papers are by Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), and a recent paper by Draca, Machin, and Witt (2008). These papers use terror (or terror warnings) as an instrument for police presence, and test whether increased police forces affect crime. More specifically, Di Tella and Schargrodsky (2004) use the incidence of a single terror attack in Argentina to estimate how the increased police presence at specific potential targets for future terrorist acts (Jewish centers) affected the reported number of car thefts around the specified targets. Klick and Tabarrok (2005) use four changes in the terror alert level in Washington D.C. to study the effect of changes in the warning level on nine different types of crime. Draca, Machin, and Witt (2008) examine the effect of police on various types of crime by using the terror attack in London in 2005 as an instrument for police deployment in London versus outlying areas in the subsequent weeks after the attack.

Similar to these papers, we use high frequency variation in the data (at the daily level) to see how terror affects crime. However, in contrast to this literature, we examine a much wider array of crimes and exploit a total of 120 fatal terror attacks to examine their effect on crime. In addition, we exploit the geographic variation of terror incidents across the entire country in order to see whether crimes are differentially affected according to whether they occurred in the same district as the terror attack or whether they occurred farther away. Finally, our study contributes to the literature by exploiting information on the location of each crime (public places versus private homes) and the relationship between the perpetrator and the victim (whether they are acquainted or not). This additional information allows us to further explore the likely channels through which terror may be affecting crime.

The next section describes the mechanisms through which terror may affect crime, while Section III describes our unique data. Section IV describes the empirical methodology. Section V presents the main results and Section VI extends the analysis by exploiting information on the location of the crime (whether the crime was committed in a public place versus a private residence) and the relationship between the victim and perpetrator (if they knew each other or not). Section VII concludes.

II. Mechanisms that May Underlie the Terror and Crime Relationship

The causal effect of police on crime has been intensely debated, although most of the recent evidence points to a negative relationship (Levitt 1997; Di Tella and Schargrodsky 2004; Evans and Owens 2007). One obvious way that terror may affect crime is through an increase in police reinforcements on the streets after an attack, which should raise the risk of apprehension. However, the magnitude of the effect may vary by type of crime (Corman and Mocan 2000). Property crimes, for example, are more likely to be affected by policing levels than crimes of violence or passion. Furthermore, the degree to which the costs of crime increase with police size should be related to the location of the crime. For example, an increasing police presence is more likely to affect crimes committed in public places (stores, parks, streets, etc) versus private homes. Thus, the strongest effects of increased policing on crime rates should be observed in property crimes and crimes that are committed in public – and the weakest for crimes of passion or crimes that occur in private homes.[1]

Empirical evidence in support of an increased police presence in response to terror is provided by Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), and a recent paper by Draca, Machin, and Witt (2008). In the Israeli context, however, police data are difficult to obtain. Therefore, we use data from the Israel Labor Force Surveys (2000-2005), which contain a random sample of individuals with information on their occupation, demographic characteristics, district of residence, labor force information in the last week, and the week of the interview. By matching the week of the interview with incidents of terror in their district of residence, we can test whether police officers increase their work hours following terror attacks. Descriptive statistics for the sample are presented in Table 1, and the regression results appear in Table 2.

The first column in Table 2 shows that a "local" terror attack (an attack with at least one fatality within the respondent's district of residence) increases the probability of working overtime by about six percentage points, after controlling for the person's age, education, number of children, sex, dummies for each year, and fixed-effects for district of residence. This is a large increase, relative to an average of only 10 percent working overtime in Table 1. However, if there was an attack with at least 5 fatalities, the probability increases by 20.2 percentage points (column 2). This effect increases to 23.5 percentage points if the attack resulted in at least 10 fatalities (column 3). In contrast,

[1] A large increase in non-police security following terror attacks, particularly outside public entertainment establishments, provides another layer of security presence that is rapidly increased following terror attacks.

Table 2 shows that attacks in districts outside of the person's residence do not affect the probability of working overtime. The last two columns confirm these patterns by showing that the probability of working overtime increases with a local attack, and the effect increases linearly with the number of fatalities. Therefore, the evidence is consistent with the idea that the Israeli police does increase its presence in areas hit by terror attacks, and in this sense, the cost of committing crime should increase as well.[2] These findings are also consistent with evaluations of policing strategies against terror within Israel (Weisburd, Jonathan, and Perry (forthcoming)).

The other mechanism through which terror may influence the costs of crime is by altering the daily routines and leisure choices of individuals in the wake of an attack. Sociologists argue that changes in routines have influenced the long-term changes in crime patterns (Cohen and Felson 1979; Cohen, Felson et al. 1980; Hipp, Bauer et al. 2004). For example, the increase in burglaries during the 1970's and 1980's can possibly been explained by the increasing tendency for both spouses to be at work during the day, thus leaving their homes vulnerable to potential criminals. This idea can be extrapolated to the present context -- the costs of crime may increase after a terror attack if more people stay at home rather than go out to bars, restaurants, and other forms of entertainment. Such a shift in leisure is consistent with the empirical evidence. Stecklov and Goldstein (2004) show that traffic volume on the roads in Israel declines for 2-3 days following an attack, with steeper declines in response to larger attacks. Becker and Rubinstein (2007) show that terror attacks induce a significant decline in bus tickets sold, expenditures on taxis, and expenditures in restaurants, coffee shops, and pubs. The

[2] It should be noted, however, that terror could reduce the costs of crime if the police concentrate more of their resources on catching terrorists as opposed to criminals.

evidence also shows that sales in a chain of Jerusalem coffee shops decline in the days following attacks, particularly in locations more open to attacks such as those in city centers (Spilerman and Stecklov 2009). In addition, they find that the decline in sales is larger after more fatal attacks. These results strongly suggest that individuals tend to stay at home after an attack and even more so after larger attacks – most likely in order to reduce their exposure to further attacks. As a result, the costs of crime increase as homes are more difficult to enter unnoticed and people tend to have more family, friends, and neighbors in the vicinity, thus providing another layer of security and protection. This mechanism, however, should primarily cause a decline in crimes committed in private residences, with little effect on crimes committed in public spaces.

Beyond affecting the cost of crime, terror may also affect the propensity to commit crime. The literature in sociology and criminology offers a variety of reasons for this, sometimes with predicted effects in opposite directions. One potential mechanism is that terror may increase social solidarity and social cohesion (National Research Council 2003; Collins 2004), which should reduce the motivation to commit crimes against fellow citizens (Cullen 1994; Landau 1997). However, an opposing effect could be produced by an increase in social stress and anxiety, leading to greater internal social conflict. Support for the idea of increased social stress comes from studies on the social consequences of natural disasters, such as Hurricane Katrina, where intense levels of social conflict and criminality were registered alongside acts of heroism and social solidarity (Tierney 2007).[3] Recent findings also point to increased levels of anxiety and stress following the September 11th terrorist attacks (Lee, Isaac et al. 2002; Schlenger, Caddell et al. 2002;

[3] Indirect support for the positive association between social stress and crime is provided by the evidence on the effect of economic stress on crime (Raphael and Winter-Ebmer 2001; Gould, Weinberg et al. 2002).

Silver, Holman et al. 2002).[4] Landau and Pfefferman (1988) present time-series evidence from Israel which is consistent with a positive association between social stress and crime. Overall, increasing stress and social solidarity generate opposite predictions on criminal behavior, but each one is likely to be more relevant for crimes involving personal interactions (assault, sexual assault, etc.) than crimes with an economic motive (property crimes).

Another potential factor on the propensity to commit crime could be due to increased risk-taking behavior in response to a prolonged exposure to terror in Israel (Pat-Horenczyk, Peled et al. 2007). This mechanism is consistent with theoretical predictions that risk-taking behavior should increase with the level of mortality risk (Liu and Rettenmaier 2007). Criminal activities, which are inherently risky, offer one natural outlet for such a reaction to terror.

Overall, our results do not show that terror increases crime levels. As such, our findings clearly refute the argument that terror increases the propensity for crime by increasing social stress or risk-taking behavior. However, the rest of the paper investigates the effect of terror in each type of crime, and assess whether the pattern of results are consistent with the mechanisms described above.

[4] In Israel, studies have shown a relatively muted response to terror when using psychological stress indicators, although there are signs of heterogeneity across different segments of the population (Bleich, Gelkopf et al. 2006; Shalev, Tuval et al. 2006).

III. The Crime and Terror Data

The main analysis is based on two primary sources of data. The first is data on criminal activity from the Ministry of Internal Security, which was obtained for the period starting from October 2000 through December 2005. Thus, the sample period starts at the beginning of the "Second Intifada", which unleashed a large wave of terrorist activity within Israel, and continues through the end of 2005 when terror attacks within Israel had mostly subsided. The crime data were obtained directly from the database of the Police Department and include every crime reported during this five year period. For each crime, information was provided regarding the date and type of crime, relationship between victim and offender (where available), geographic location of the crime (name of the locality), and type of location (residential building, commercial property, street, etc). The file includes information on a total of 3,279,882 incidents of crime spread out over 158 different types of crime. Each day, an average of 1,619 incidents of crime are reported to the police.

Because many of the crimes in the database rarely occur, we concentrate our analysis on 13 specific types of crime which can be classified more broadly into four main categories: property crimes (burglary, robbery, auto theft, and "theft from an auto"), violent crimes (murder, assault, and aggravated assault), sexual crimes (rape and sexual assault), and crimes of public disobedience (trespassing, public disorder, attacking or disrupting the police, and disturbing the peace).[5] Use of these categories, which are the

[5] In addition to being rare, many of the detailed types of crime (spying, blackmail, etc.) are unlikely to be related to a specific event on a given day. Other crimes like bribery may be assigned a specific date of occurrence, but the crimes themselves and the lag between when they were planned and carried out will make it very difficult to expect any relationship to terror attacks.

most common types of crime, allows us to examine whether the effect of terror on crime depends on the motives underlying the crime. For example, property crimes are primarily motivated by financial gain, while violent and sexual crimes have little to do with monetary incentives. These latter crimes are motivated more by personal conflicts and psychological issues, and therefore, we expect that they will be *less* affected by the costs associated with an increasing police presence than property crimes. Variation in the motives behind each of these types of crimes will allow us to see not only if terror affects crime, but also to illuminate the likely channels.

Table 3 presents summary statistics for the crime data.[6] The most prevalent types of crimes are "theft from an auto", burglary, and assault. Lagging much further behind these three categories are auto-theft, trespassing, and public disorder. The least common crimes are murder, aggravated assault, robbery, rape, sexual assault, and attacking the police. Similar to many other countries, the incidence of a particular type of crime decreases with its severity. Therefore, although rape and murder may occur very infrequently, the high social cost of these types of crimes make them worthwhile to analyze.

In order to better understand the causality between terror and crime, we exploit several aspects of our unique data. In particular, we utilize information on the location of each incident of crime and terror, by dividing the country into 17 subdistricts (the West Bank and Gaza Strip are not included).[7] Information on the geographic location of the

[6] Distinct crime categories are constructed for rapes, sexual assaults and murders that are between persons acquainted with each other. We include these as separate crimes and discuss them further below.
[7] The list includes Jerusalem, Tsfat, Kineret, Afula, Acco, Nazareth, Haifa, Hadera, Sharon, Petach Tikva, Ramle, Rehovot, Tel Aviv, Ramat Gan, Holon, Ashkelon, and Beer Sheva.

crime enables us to test whether terror attacks within a given location have a differential effect on the local crime rate versus attacks occurring throughout the rest of the country. Differential effects could be expected if police forces are disproportionately increased in the area where the attack occurred. This pattern would be exacerbated if the increased police force in the area which suffered the attack came at the expense of lowering the police presence in unaffected areas. Also, information on the location of each crime and terror attack allows us to control for any spurious correlation between the local crime rate and the propensity to be attacked by terrorists. For example, it may be the case that Jerusalem has a high crime rate and also is a frequent target for terrorists. Our analysis controls for the location of the crime, and therefore, neutralizes any spurious correlation between local crime rates and the propensity to be attacked.

We also exploit variation in the "type of location" (street, public building, private residence, etc) where each crime was committed. For most types of crime, we distinguish between those that were committed in a public space versus those that were committed in a private residence. (Public spaces include all places except private residences and yards.) For example, a burglary could be committed against a store, which is public, or from a private residence. Table 3 breaks down the frequency of each crime by the type of location. A few of the crimes are committed primarily in public places (attacking the police, robbery, auto-theft, and theft-from-auto), but most other crimes occur in both public and private places. After a terror attack, the police routinely increase their presence, particularly in the area where the attack occurred and other sensitive targets. Our strategy of differentiating between crimes committed in public versus private spaces allows us to examine whether the effect of terror on crime is similar across types of crimes and types of locations, shedding light on whether the evidence is consistent with an increasing level of police presence on the street as opposed to more people simply staying home.

The third characteristic of each incident of crime that we exploit, the relationship between perpetrators and victims, provides another perspective on the causal link between terror and crime. Recent studies in the criminological literature have emphasized the role of acquaintanceship in certain types of crimes, such as murder (Haynie and Armstrong 2006) and rape (Fisher, Cullen et al. 2005; Pazzani 2007). For both types of crime, there are important differences separating incidents committed by someone who knows the victim and incidents between strangers. Crimes where the victim and perpetrator know each other are more likely to be driven by changes in stress levels due to terror attacks. A priori, we would expect stress-related crimes between persons acquainted with each other to increase as people spend more time together at home.[8]

The data on terror incidents is obtained from two sources: the database of the Interdisciplinary Center of Herziliya and the database of Be'etselem, a human rights organization in Israel. We include all terror attacks with at least one fatality (not including the terrorist) that took place within Israel, excluding the West Bank and Gaza. We classify terror incidents into two overlapping levels of severity: all attacks with 1 or more deaths; and large attacks with 5 or more deaths. The timing and number killed in each of the terror attacks included in our data are shown in Figure 1.

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[8] However, using this information forces us to restrict the analysis in this case to those crimes where the perpetrator is known, since in many cases the perpetrator is unknown until and if the crime is solved.

Figure 1 clearly shows large variation in the incidence and severity of daily attacks which can be exploited to explain variation in various crime rates over time. There are a total of 615 fatalities during the sample period that resulted from 120 separate attacks where at least one person was killed. Of these 120 attacks, there were 45 large attacks with at least 5 fatalities. These unfortunate events provide a lot more variation to exploit than data used by previous studies (i.e. Di Tella and Schargrodsky 2004; Klick and Tabarrok 2005). The distribution of fatal terror attacks across the 17 regions along with the average number of fatalities per attack is displayed in Table 4.

IV. The Basic Regression Model

With data on daily terror incidents and reported offenses for each category of crime, the basic empirical strategy is to regress the daily number of offenses for a particular type of crime on dummy variables indicating whether a terror attack occurred on the same day or on previous days. In addition, we allow for the effect of a terror attack on criminal activity to differ between areas that are close to the attack and areas that are farther away. We expect all the potential mechanisms described in Section II to be more salient in areas closer to the attack, but all of them could be relevant, albeit less so, in areas further away from the attack. For every individual crime category (we suppress the subscript for type of crime), the basic regression specification is the following distributed lag model:

$$Crime_{it} = \alpha + \sum_{k=0}^{n} \beta_{t-k}^{L} L_{i,t-k} + \sum_{k=0}^{n} \beta_{t-k}^{NL} NL_{i,t-k} + \gamma Z_t + \mu_{it} + \varepsilon_{it}$$

where $Crime_{it}$ is the reported number of criminal offenses (for a given category of crime) in location i on day t, $L_{i,t-k}$ = 1 if there was a bombing on day t-k in location i and 0 otherwise, $NL_{i,t-k}$ = 1 if there was a bombing on day t-k in a location other than location i (non-local) and 0 otherwise, μ_{it} is the fixed-effect for location i during the year and month that contains day t, and Z_t is a vector of exogenous explanatory variables including dummy variables for each day of the week and major holidays[9]. The latter variables control for potential confounding factors which could arise from the tendency for crime and terror attacks to take place on specific days of the week or during holiday seasons. After experimenting with the appropriate lag structure, it seemed appropriate to stop with five lags.

The regression specification above includes a fixed-effect for each location and month in the sample. That is, the model includes 1071 fixed-effects, one for every combination of 17 localities and 63 months (October 2000 through December 2005).[10] To the extent that terror attacks are concentrated in certain areas (like Jerusalem and Tel Aviv), a spurious correlation between terror attacks and criminal activity could exist if these same localities are also different from the rest of the country in terms of their criminal activity. Inclusion of a fixed-effect for each locality appears warranted given that the most popular targets for terrorists are often the largest and most dense population

[9] The standard error estimates of our estimators will tend to be smaller for non-local estimates simply because they are based on more information. This point is worthy of noting when assessing the results for local and non-local coefficients in the next section.

[10] In certain cases, a fixed-effect for a particular district-month was dropped by the regression if the dependent variable was zero for the whole month. For example, in many cases, there are no murders in a given month within a given subdistrict. Therefore, the total number of potential observations for the regressions in Table 6 is 32,606, but this was the actual number of observations for assault, burglary, auto-theft, theft-from-auto, public disorder, and disrupting the police. The sample size for the other crimes were: 17,189 for murder; 7,203 for murder between acquaintances; 32,547 for aggravated assault; 29,893 for robbery; 32,056 for trespassing; 24,880 for disturbing the police; 29,443 for rape; 24,753 for rape between acquaintances; 32,239 for sexual assault; 27,378 for sexual assault between acquaintances.

centers of the country, and because of the general positive relation between larger cities and crime (Glaeser and Sacerdote 1999).

However, the model specification goes much further by including a fixed-effect for each month and locality. By doing this, we control not only for differences across locations in their levels of crime and terror, but we allow for differences in the trends of crime and terror across localities in a very flexible way (a step function for each of the 63 months within each locality). Over the five-year period studied, one might expect that the government adjusted the size and tactics of the local police force to the trend in the local level of terror. If true, then a spurious correlation could exist between the local trends in criminal activity and terror. Therefore, the overall empirical strategy is to exploit very high frequency variation in the data – the effect of terror on crime is identified by seeing whether the crime rate is different on days with terror versus days with no terror within a given month in a given locality (while controlling for day of the week and holidays).

Since we are exploiting variation at the daily level, it is often the case that there are no crimes on a given day in several locations. That is, there are many cases where the dependent variable is zero. Given the "count data" nature of the dependent variable, we use a Poisson model to estimate the equation above and our results are presented in terms of proportional effects. Tests to evaluate the appropriateness of the Poisson distributional assumptions turned out to be generally consistent with the data, and therefore, alternatives such as the negative binomial regression are not presented. However, it is worth noting that the general pattern of results presented using the Poisson specification were found using the negative binomial model and a standard OLS regression with fixed-effects. Also, although we present only the results with fixed-effects for each location-month-year, qualitatively similar results were obtained using fixed-effects only for location (with aggregate time trends included as controls).

V. Main Results

Table 5 presents the main results for all 16 crime categories (13 types of crime plus 3 additional variables for crimes between persons acquainted with each other) when we test only for a contemporaneous effect of terror attacks that are local and non-local on the crime rate on the day of the attack. In addition, our results are presented using two alternative ways of defining a terror attack. The first definition includes any attack with at least one Israeli civilian fatality ("all attacks"). The second counts only attacks where at least five Israeli civilians were killed ("large attacks"), which is just about the mean level of fatalities per attack (mean equals 5.2) in our sample.

We initially estimated each model by allowing for an immediate effect on crime on the day of the attack, and allowing for a lagged effect for up to five days after the attack. The results of these models are displayed in the Appendix in Tables A1-A4. Table 6 estimates a more parsimonious model by explaining each daily crime rate with a dummy variable for having a local attack on day t or the previous five days, and a dummy variable for having a non-local attack on day t or the previous five days. Given our primary interest in estimating the direction of the short-term effect of terror on crime rather than the specific temporal pattern within this short time window, we confine our discussion of the results to Table 6 which summarizes the effect of having an attack that day or during the previous five days.[11]

Public Behavior Crimes

For crimes related to public behavior, the main result in Table 6 is that a terror attack within the last five days increases incidents of trespassing, regardless of whether the attack was local or non-local. The coefficient for a local attack is 0.052, which implies that any fatal terror attack increases trespassing by an average of 5.3 percent (which equals exp(0.052)) for each of the following five days. However, the coefficient is not significant, nor are most of the other coefficients for public behavior crimes. The only exception is the large and very significant positive effect of non-local terror on trespassing. In contrast, large attacks produce significant increases in trespassing following both local and non-local terror, although the coefficients are similar in magnitude to those obtained for "all attacks." Table 6 shows that crimes like "public disorder" or "disturbing the peace" do not respond to terror attacks regardless of whether they are large or small. However, incidents of "disrupting the police" increase following all types of attacks, but are significant only for large attacks.

Overall, the results for public disobedience crimes are consistent with a higher police presence on the streets after a terror attack. More police officers on the streets will naturally lead to more arrests for trespassing, since someone typically needs to catch someone in the act in order to make an arrest. Also, a higher level of policing could explain the increase in "disrupting the police," since more police on the streets will create

[11] Appendix Table A5 performs the same analysis presented in Table 6, but does so at the district level (which was done in Table 2 for the analysis on police overtime), rather than the subdistrict level. The results are very similar to Table 6.

a larger number of incidents of contact between civilians and police officers. However, this result could be due to a higher level of alert by police officers on duty, which increases the likelihood that they issue an arrest for a given incident. The lack of any effect for "public disorder" or "disturbing the peace" suggests that there is no evidence in favor of a large change in the public behavior of normal citizens following an attack. That is, there does not seem to be any evidence that an increase in stress levels or social solidarity is affecting behaviorally motivated crimes in one direction or the other.

Property crimes

The strongest response that we find in relation to terror attacks is with property crimes, which are also the most prevalent types of crimes. A terror attack in the last five days has a large and negative effect on burglaries, auto-thefts, and "thefts-from-autos." The estimates imply that a local attack reduces the burglary rate by 6.5 percent for each of the five days following an attack (approximately 9.96 burglaries relative to a mean of 153.27, which is almost of third of a standard deviation of 34.99 in Table 3). The magnitude of the effect is similar for thefts-from-autos (5.8 percent reduction), which is about 9.75 offenses relative to a mean of 168.14, which is also almost a third of a standard deviation of 32.84 in Table 3. However, the estimated coefficient is considerably higher for auto-thefts – a 12.6 percent reduction in auto-thefts for each of the five days after any terror attack. The estimated magnitude is about 10.16 auto-thefts relative to the mean of 80.66, which is more than half of a standard deviation of 18.23.

Overall, the results for these three property crimes are significant for both local attacks and non-local attacks, and whether we look at all attacks or "large attacks". However, two clear patterns emerge for property crimes. First, the effect of a local attack is much larger than the effect for non-local attacks. For example, the coefficient for a local attack is 3 times larger than a non-local attack for burglaries, 6 times larger for auto-thefts, and 3-4 times larger for thefts-from-autos. This pattern highlights the need to distinguish between local and non-local attacks. The second pattern evident in Table 6 is that larger attacks yield larger responses in crime, particularly for local attacks. This is true for all property crimes – the coefficient for "a large attack" is bigger than "any attack" by a factor of 1/3 for burglaries, 2 for auto-thefts, and 1/3 for thefts-from-autos.[12] Finally, although the effect of a local attack seems to increase with the size of the attack, this pattern is not as evident for non-local attacks.

Once again, these findings are consistent with an increasing deterrence effect of a larger police presence after a terror attack. It is reasonable to expect not only a larger general police deployment after a terror attack, but also that the forces will be disproportionately placed in areas that suffered the attack (as shown in Table 2). Also, Table 2 indicates that the police response increases with the size of the attack. These patterns can explain the results displayed in Table 6 -- larger reductions in crime in the area where the attack occurred and larger effects after larger attacks.[13]

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[12] In results that are not presented, we found that the reduction in auto-thefts and thefts-from-autos is sharper as the number of casualties in the last five days increases. The number of casualties was not significant for other types of crime.

[13] The decline in auto thefts could be partially due to the Israeli army closing the border to the West Bank and Gaza Strip after a terror attack, but the results are robust to including measures for closures into the regression.

In contrast to the other property crimes, robbery does not seem to respond in any systematic way after a terror attack. However, it is important to note that burglary, auto-theft, and thefts-from-autos are among the most prevalent categories of crime. Burglaries are 25 times more common than robberies, and theft-from-autos is even more prevalent than burglaries. As the fourth most common type of crime, auto-thefts are also very influential on the overall crime rate. Therefore, the results in Table 6 indicate that the overall property crime rate declines significantly after a terror attack.

Sex Crimes

Table 6 shows that terror does not have any systematic effect on sex crimes. The coefficient for a local attack on rape is significant and quite large – suggesting an increase of 17 percent in the five days after a local attack. However, in contrast to the patterns for property crimes, the effect is much smaller and insignificant for large attacks and is not significant at all for non-local attacks. The lack of any systematic pattern in relation to the size of the attack makes us particularly reticent to place much value on this coefficient. In addition, after examining the coefficients for each of the five days after an attack (Table A3), the significant positive coefficient in Table 6 is seen to mask a complex pattern where there is a dramatic decrease in rapes the day after an attack (a 60 percent decline), and then there is a sharp increase on day 3 and day 4 after an attack (50.3 percent and 44.6 percent respectively). Since rape is unlikely to be affected by the local police presence, this "down-and-up" pattern could be due to an initial increase in social solidarity followed by increasing stress levels. However, we find no such pattern for sexual assaults. In fact, large attacks are shown in Table 6 to decrease sexual assaults in the next five days. These conflicting results for similar types of crimes cast doubt on whether the results for rape are driven by a few random outliers – a realistic concern given that rapes are relatively rare and only one-third as frequent as sexual assaults (see Table 3). Therefore, the lack of significant results for most of the sexual crimes, combined with an inconsistent pattern for the few coefficients that are significant, lead us to conclude that terror did not produce any systematic effect on sexual crimes.

Violent Crimes

Table 6 presents results for three types of violent crimes: murder, assault, and aggravated assault. The large increase in murders following an attack draws particular attention, but this result is most likely spurious. Although the Israeli Police report that deaths from terror attacks are not supposed to be included in the murder category, the evidence suggests that in most cases fatal terror attacks were recorded as a murder of one person. (The mean number of murders on days without a terror attack is 0.027, while the mean number of murders on days with terror is 0.842). Further evidence that the large murder effect is due to data misclassification is that the effect of terror on murder is entirely contemporaneous, with no systematic pattern in the days following the terror attack (see Table A4). Table 6 also shows an increase in murders when the attack is non-local, which is somewhat believable since a terror attack occurring in locality j may be recorded as a murder in locality j, but not in locality i. Given that a large proportion of murders in Israel are mob-related, the mafia might conceivably use the confusion induced by a terror attack as an opportunity to settle scores. However, we tend to discount the murder results due to the obvious classification error problems.

Another cause for skepticism regarding the increase in murders is that there are no similar increases in other violent crimes like assaults and aggravated assaults. If increased social stress were driving the murder results, a general increase in other forms of violent crime should be discernible. However, Table 6 shows a significant decline of 13.2 percent in aggravated assaults for five days following any local attack. This reduction is larger, 17.8 percent, for larger local attacks. That is, the results for aggravated assault show a similar pattern exhibited by property crime: a larger decline in response to local attacks versus non-local attacks, and a stronger response to larger attacks. Similar to the decline in property crime, the decline in violent crime is likely a result of an increasing cost of crime. However, in the case of violent crime, the increase in costs is likely driven by the shift in leisure activities as much as it is by increased policing. Of course, the decline in violent crimes may conceivably be driven by behavioral responses, such as an increasing sense of social solidarity after an attack, but this argument looks less likely following the analysis presented in the next section.

VI. Extensions of the Main Results

Does Familiarity Matter?

As already noted, the data contain information on the relationship between the victim and the perpetrator (when it is known). Crimes committed between individuals who previously knew each other are more likely to be influenced by personal tensions between the two parties than an incident between two strangers. Therefore, we expect that the existence of a strong behaviorally motivated response in crime to be identifiable by focusing on crimes between acquaintances. In Table 6, we show additional results for murder, rape, and sexual assault – but only for incidents that occur between acquaintances. The results for each of the five days after an attack are shown in the Appendix Tables.

Although we found a few significant results for the overall categories of rape and sexual assault, the results are generally weaker when we look only at those committed between acquaintances. We do find strong effects once again for murder between acquaintances, but this result remains suspect for reasons stated earlier.[14] Overall, the results provide no support for the idea that terror induces an increase or decrease in tensions between friends, spouses, and acquaintances.

Does the Type of Location Matter?

A central feature in our data is the ability to distinguish between crimes committed in public places and crimes committed in private residences. Distinguishing crimes by the type of location in which they occur offers further insight into the relevance of possible mechanisms behind our findings. For example, a heavier police presence is likely to raise the costs of crimes committed in public more than it raises the costs of

[14] We hoped that we could extract from the problem of coding terror attacks as murders by looking only at murders between acquaintances. However, we obtained similarly suspicious results, most likely because a few terror incidents did involve a terrorist who knew his victim (a worker and his employer).

crimes committed in private homes, while crimes committed at home are more likely influenced by the increased time spent at home because people go out less to restaurants and other leisure activities after terror attacks.

Tables 7 presents the effect of any terror attack on each type of crime after dividing each category of crime into those committed in "public" versus those committed in private residences ("at home"). The positive effects of a terror attack on trespassing and “disrupting the police” are notably more pronounced in public places versus private residences. That is, the generally positive effects shown in Table 6 for both crimes appear driven by the effect of terror on the crimes committed in public places. This result is consistent with the interpretation that a higher police presence following an attack is leading to higher rates of arrest and generally more incidents of contact between civilians and police officers.

The results for property crime are generally stronger for those committed at home versus in public places, although significant effects are found in both types of locations. The estimates for local attacks on burglaries and auto-thefts are much stronger in private homes versus public places, emphasizing the argument that the shift in leisure activities is playing a role in increasing the costs of crime. However, local attacks are still highly significant for auto-thefts in public, and non-local attacks are significant for burglaries and auto-thefts in public. In fact, non-local attacks actually have larger effects on burglaries and auto-thefts in public places versus private homes. The results for theft-from-autos are much more significant in public places versus private homes for both local and non-local attacks. The coefficient magnitudes are higher for private places, but they are not significant.

Overall, the significant effects for property crimes committed in public places is once again evidence in favor of the deterrence effect of an increased police presence. The fact that the effects are larger in magnitude for burglaries and auto-thefts in private homes is consistent with a larger police presence, but also supports the notion that there is a deterrent effect on crime when people shift their leisure time towards home-based activities.

The results do not show systematic effects of terror on sexual crimes committed in public or private places. However, there are interesting distinctions for violent crimes in Table 7. Specifications in Table 6, which did not distinguish between crimes in public versus private, yielded insignificant results for assaults. After making the public-private distinction in Table 7, the results now show significant reductions in assaults in private places. These findings suggest that terror might also raise the costs of violent crimes by keeping people and their family and friends nearby. While increasing time at home could potentially aggravate crimes such as domestic disturbances, there is no evidence to suggest that this is occurring.

Finally, Table 8 presents a similar breakdown of each crime into public and private, but considers only "large attacks" as incidents of terror. Overall, the results are similar to those obtained in Table 7, which looked at all terror attacks. However, the results tend to be larger when we look at larger attacks, although the standard errors also appear larger so the significance is sometimes lower.

Distinguishing Between Nearby and Far Away Attacks

So far, we have distinguished only between local and non-local attacks in our regression specifications. Here, we investigate the spatial dimension of the effect of terror in more detail by dividing non-local attacks into two categories: those that occur nearby in an adjacent subdistrict and those that occur farther away in a non-adjacent subdistrict. The effect of terror could differ if police officers and other resources are shifted from nearby areas into the area where the attack occurred – thus affecting the costs of crime differentially across space according to the proximity of the attack. However, the results in Table 9 suggest that the effect of non-local attacks are either similar (trespassing and burglary) or get weaker (auto theft and theft from autos) with distance from the attack. This pattern is not consistent with resources being shifted to nearby areas that are attacked, which would have caused a relative increase in crime in contiguous areas versus areas further away. Overall, the pattern of results is quite similar for non-local attacks in adjacent subdistricts versus those in subdistricts further away.

VI. Conclusion

Using a unique panel data set on the daily criminal and terrorist activity in 17 districts in Israel from October 2000 through 2005, this is the first paper to analyze the effect of an extended wave of terror on various categories of criminal activity. After controlling for the fixed-effect of each district and for district-specific time trends, our results show that terror reduces property crimes such as burglary, auto-theft, and thefts-from-cars. It should be noted that burglary and thefts-from-cars are the two most common types of crime, and auto-theft is the fourth most common (assault is number three).

We also find that terror attacks reduce incidents of assaults and aggravated assaults that occur in private homes. In contrast, terror attacks increase crimes committed in public spaces such as trespassing and disrupting the police. Generally speaking, the estimated effects for all crime categories increase with the size of the terror attack, and local attacks have a larger effect on local crime rates than non-local attacks.

Overall, the pattern of results appears to be driven by the increased costs associated with criminal activity following terror attacks. An increased police presence following terror attacks is consistent with a stronger deterrence effect for property crimes (burglary, auto-theft, and theft-from-autos) [15], while at the same time increasing incidents of trespassing and "disrupting the police." The latter effect could be considered an expected outcome when more police are on the streets, since more trespassing and disruptions of police work are expected when the police are increasing their surveillance operations. Indeed, our analysis shows that the police increase their presence more in the area where a terror attack occurs versus other areas, and that the response increases with the size of the attack. This behavior by the police is consistent with our findings that the effects of terror on crime are larger in the area of the attack, and even more so when the attack causes more fatalities.

[15] One possible confounding factor could the that the Israeli Defense Force often erects barriers and institutes closures on the West Bank and Gaza Strip after a terror attack, and the closure typically lasts at least a few days. However, in results not presented, we tested this hypothesis by including dummy variables for days when a closure was in progress, and the results turned out to be very similar.

However, the costs of crime may also increase after an attack due to shifts in leisure activities – an increased tendency to stay at home after an attack. While increased policing may be able to explain some of the decrease in property crime in private homes, it is also likely that there is increased deterrence when more people are staying at home. That is, the increased presence of family and friends in their own homes and nearby houses offers an effective additional layer of security against criminals. Similarly, the decline in violent crimes, primarily in private spaces, may be influenced by the fact that family members and friends are providing additional support and security at home. Since we do not find a significant increase in police presence in response to non-local attacks, it is possible that the significant effect of non-local attacks on certain crime rates may be due entirely to the increasing costs of crime resulting from a shift in leisure activities.

Our results reject the hypothesis that terror increases the propensity to commit crime by increasing social tensions. In addition, the evidence is inconsistent with the idea that terror lowers the cost of crime by taking away police resources from crime-fighting activities.[16] Although increased social cohesion could explain the observed reduction in crimes, it seems likely that this factor plays a limited role. An increase in social solidarity clearly cannot explain an increase in public crimes such as trespassing and disrupting the police. Given our expectation that social cohesion will have a stronger impact on violent

[16] A possible explanation for our results could be that terror attacks make individuals less likely to report criminal activity to the police. We believe the evidence is not consistent with this explanation for several reasons. First, it should be noted that the date of each crime in our data set is not the date that it was reported, rather, the day the crime was committed. So, if people delay reporting the crime for a day or two, this would not affect the results. Second, although people may try to avoid calling the police on the day of a terror attack to report a crime, it seems unlikely that this could explain the decline in crime for up to five days after an attack. Third, the tendency to under-report in reaction to terror should be stronger for less serious types of crime, since individuals should be more likely to report serious crimes regardless of whether there was an attack or not. But, we do not see a decline in small crimes like "disturbing the peace" which we would expect people to under-report on days of an attack, and we do not see a larger decline in "assaults" versus the more serious "aggravated assaults" in private homes.

and sexual crimes relative to crimes with an economic motive, rising social solidarity is not likely to be a factor in the large reduction in property crimes. In fact, the only real question is whether increasing social solidarity can explain the decline in violent crimes. For this effect to be convincingly demonstrated, it would need to be reflected in a decline in similar crimes in public spaces – places where the social interaction of strangers might be modified by increasing solidarity. However, assaults in public places actually show a slight increase after an attack. The entire decline in violent crime is limited to private residences, thus providing little support for the social solidarity effect.

Overall, our results are consistent with those in Di Tella and Schargrodsky (2004), Klick and Tabarrok (2005), and Draca, Machin, and Witt (2008) in the sense that we also show that terror leads to a significant reduction in crime. However, our analysis exploits a much larger number of terror attacks, and examines a larger set of crime categories. In addition, our results differ from Di Tella and Schargrodsky (2004) in that we show a general decline in property crime throughout the country in response to a terror attack, while they show a decline in auto thefts in Argentina only around areas which were regarded as potential targets, and therefore, received extra police protection. This difference in results is likely due to the limited way that police forces were bolstered only around Jewish areas in Argentina, while in Israel, policing had to be increased more widely because everyone was a potential target and the socio-behavioral impact would also be expected to affect the population more widely than in Argentina.

As a result, our analysis suggests that increasing the costs of crime on a wide scale, through increased police presence on the street as well a shift in the day-to-day activities of people, can have a substantial impact on some of the most common types of crime. Terrorists appear to increase the costs of crime in both of these dimensions, and therefore, impose a severe negative externality on potential criminals.

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Figure 1: Daily Count of Fatalities from Terror in Israel
(excluding the West Bank and Gaza) from 1/10/2000-31/12/2005

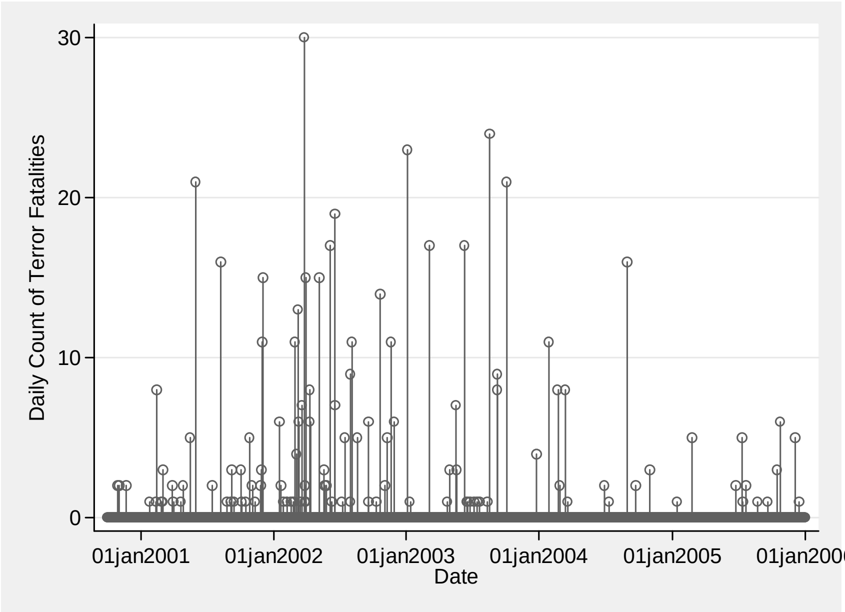

Table 1: Descriptive Statistics of the Police Overtime Data by Week, 2000-2005

	Mean	Std.
Worked Overtime During the Week	0.11	0.31
Age	36.03	8.57
Education	13.54	1.83
Male	0.84	0.36
Any Terror Local Attack (≥1 Fatality) during the Week	0.06	0.23
Large Terror Local Attack (≥5 Fatalities) during the Week	0.02	0.14
Very Large Local Terror Attack (≥10 Fatalities) during the Week	0.01	0.11
Number of Observations	1073	

Notes: The sample consists of individuals currently working as police officers in Israel from the Israel Labor Force Surveys from 2000-2005.

Table 2: Effect of Terror on Police Overtime Work during the Same Week

	Marginal Effects Probit on Working Overtime During the Week				
Local Attack (≥1 Fatality)	0.0649** (0.025)			-0.00761 (0.036)	-0.00926 (0.040)
Non-Local Attack (≥1 Fatality)	0.00133 (0.014)				0.00163 (0.018)
Local Attack (≥5 Fatalities)		0.202* (0.11)			
Non-Local Attack (≥5 Fatalities)		-0.0115 (0.029)			
Local Attack (≥10 Fatalities)			0.235** (0.12)		
Non-Local Attack (≥10 Fatalities)			-0.0113 (0.021)		
Number of Local Fatalities				0.0102* (0.0056)	0.0102* (0.0057)
Number of Non-Local Fatalities					0.000284 (0.0016)
Observations			1073		

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. All regressions include a fixed-effect for each of the six districts in Israel (Jerusalem, Northern, Haifa, Central, Tel Aviv, and Southern districts), dummies for each year from 2001-2005, years of schooling, age, age squared, sex, and number of kids in the following ranges: 0-1, 2-4, 5-9, 10-14, and 15-17. Local attacks are those occurring in the respondent's district, and non-local attacks are those outside of the respondent's district. Standard errors are clustered at the district level.

Table 3: Summary Statistics on Incidents of Crime, Israel 2000-2005

	All Locations		No Terror Past 5 days	Terror Past 5 days	Private Homes	Public Places
	Daily Mean	Daily Standard Deviation	Daily Mean		Daily Mean	
Trespassing	46.17	22.54	45.87	46.88	2.30	43.88
Public Disorder	36.07	17.39	36.09	36.02	17.95	18.12
Attack Police	16.06	5.20	16.14	15.88	1.38	14.68
Disturb Police	2.79	2.14	2.72	2.95	1.43	1.35
Burglary	153.27	34.99	155.28	148.53	95.26	58.00
Robbery	6.03	2.78	6.12	5.82	0.86	5.17
Auto Theft	80.66	18.23	82.42	76.52	4.04	76.62
Theft from Auto	168.14	32.84	168.72	166.76	1.09	167.05
Rape	2.06	2.59	2.08	2.02	1.27	0.79
Rape Acquainted	1.10	1.67	1.11	1.08	0.87	0.23
Sexual Assault	6.31	7.06	6.31	6.32	2.15	4.16
Sexual Assault Acquainted	1.98	3.50	1.97	1.99	1.15	0.83
Murder	0.50	0.72	0.44	0.66	0.15	0.35
Murder Acquainted	0.15	0.39	0.14	0.19	0.08	0.08
Assault	113.33	24.78	112.64	114.98	53.06	60.27
Aggravated Assault	8.44	3.46	8.52	8.26	4.22	4.22

Table 4: Terror attacks by subdistrict

Subdistrict	Number of Fatal Attacks	Average Fatalities per Attack
Jerusalem	41	5.2
Zefat	1	9.0
Kineret	0	0.0
Afula	11	3.8
Acco	3	3.3
Nazareth	1	1.0
Haifa	6	12.8
Hadera	12	4.0
Sharon	11	5.2
Petach Tiqwa	10	1.6
Ramle	0	0.0
Rehovot	3	8.7
Tel Aviv	13	6.2
Ramat Gan	1	1.0
Holon	0	0.0
Ashqelon	4	3.0
Beer Sheva	3	6.7

Table 5: Contemporaneous Effect of a Terror Attack on Crime, Israel 2000-2005

	All Attacks				Large Attacks			
	Trespass	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**	**Trespass**	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**
Local Attack	0.150**	0.0553	0.160*	0.0763	0.0730	0.0536	0.166	0.0132
	(0.060)	(0.075)	(0.083)	(0.20)	(0.069)	(0.16)	(0.11)	(0.43)
Non-Local Attack	0.0949***	0.0387	0.0339	0.115*	0.127***	0.0228	0.0322	0.224**
	(0.023)	(0.024)	(0.032)	(0.068)	(0.037)	(0.034)	(0.042)	(0.10)
	Burglary	**Robbery**	**Auto Theft**	**Theft from Auto**	**Burglary**	**Robbery**	**Auto Theft**	**Theft from Auto**
Local Attack	-0.0812***	-0.0626	-0.143***	-0.0620*	-0.180***	0.138	-0.339***	-0.0530
	(0.030)	(0.15)	(0.049)	(0.036)	(0.052)	(0.26)	(0.083)	(0.041)
Non-Local Attack	-0.0178*	-0.0157	-0.0116	-0.0157*	0.00363	-0.0101	-0.0378**	-0.0200
	(0.011)	(0.045)	(0.012)	(0.0095)	(0.014)	(0.063)	(0.019)	(0.013)
	Rape	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**	**Rape**	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**
Local Attack	0.155	0.123	-0.130	-0.0315	0.447	0.365	-0.171	-0.478
	(0.25)	(0.34)	(0.21)	(0.30)	(0.34)	(0.40)	(0.24)	(1.98)
Non-Local Attack	0.0817	0.109	0.0779*	0.146*	0.0905	0.111	0.146*	0.106
	(0.070)	(0.10)	(0.043)	(0.079)	(0.11)	(0.16)	(0.089)	(0.15)
	Murder	**Murder Acq.**	**Assault**	**Aggravated Assault**	**Murder**	**Murder Acq.**	**Assault**	**Aggravated Assault**
Local Attack	3.383***	3.436***	-0.0241	-0.111	3.186***	3.616***	-0.0488	-0.177
	(0.097)	(0.30)	(0.039)	(0.15)	(0.16)	(0.41)	(0.10)	(0.21)
Non-Local Attack	0.287***	0.115	0.0152	-0.0670*	0.0832	0.116	-0.0131	-0.0573
	(0.10)	(0.20)	(0.011)	(0.039)	(0.25)	(0.36)	(0.016)	(0.064)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Table 6: Effect of Terror in the Last 5 Days on Crime by Size of Attack, Israel 2000-2005

	All Fatal Attacks				Large Attacks			
	Trespass	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**	**Trespass**	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**
Local Attack	0.0519	-0.00878	0.0766	0.00324	0.0743*	-0.0274	0.0668*	-0.0964
	(0.036)	(0.032)	(0.049)	(0.090)	(0.044)	(0.043)	(0.036)	(0.18)
Non-Local Attack	0.0785***	-0.00630	0.0192	0.0112	0.0612**	0.0162	0.0448**	0.0271
	(0.019)	(0.014)	(0.018)	(0.033)	(0.025)	(0.015)	(0.022)	(0.044)
	Burglary	**Robbery**	**Auto Theft**	**Theft from Auto**	**Burglary**	**Robbery**	**Auto Theft**	**Theft from Auto**
Local Attack	-0.0675***	0.000817	-0.135***	-0.0599***	-0.0927**	0.118	-0.275***	-0.0832**
	(0.018)	(0.079)	(0.023)	(0.020)	(0.039)	(0.12)	(0.035)	(0.037)
Non-Local Attack	-0.0270***	0.0117	-0.0280***	-0.0162**	-0.0271***	-0.00192	-0.0337***	-0.0192*
	(0.0067)	(0.023)	(0.0076)	(0.0070)	(0.0083)	(0.031)	(0.011)	(0.012)
	Rape	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**	**Rape**	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**
Local Attack	0.176**	0.120	-0.102	0.0393	0.0949	0.0229	-0.236*	-0.208
	(0.081)	(0.14)	(0.066)	(0.14)	(0.13)	(0.23)	(0.13)	(0.20)
Non-Local Attack	-0.0348	-0.0394	0.0170	-0.000484	-0.0705	-0.0699	0.0157	-0.0426
	(0.040)	(0.059)	(0.027)	(0.055)	(0.050)	(0.081)	(0.041)	(0.067)
	Murder	**Murder Acq.**	**Assault**	**Aggravated Assault**	**Murder**	**Murder Acq.**	**Assault**	**Aggravated Assault**
Local Attack	1.661***	1.685***	-0.0235	-0.142**	1.574***	2.249***	-0.0126	-0.196*
	(0.11)	(0.21)	(0.018)	(0.072)	(0.17)	(0.40)	(0.028)	(0.10)
Non-Local Attack	0.0148	-0.160	0.00375	-0.0184	0.0562	0.134	-0.00585	-0.0311
	(0.082)	(0.16)	(0.0057)	(0.021)	(0.11)	(0.15)	(0.0087)	(0.030)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Table 7: The Effect of Any Terror Attack in the Last 5 Days on Crime by Type of Location, Israel 2000-2005

	Home				Public			
	Trespass	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**	**Trespass**	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**
Local Attack	-0.110	-0.0113	-0.0795	0.103	0.0575*	-0.00614	0.0852**	-0.0869
	(0.10)	(0.048)	(0.13)	(0.13)	(0.033)	(0.039)	(0.036)	(0.13)
Non-Local Attack	0.0740	0.00232	0.0426	-0.000119	0.0789***	-0.0157	0.0169	0.0251
	(0.051)	(0.017)	(0.054)	(0.053)	(0.015)	(0.016)	(0.017)	(0.062)
	Burglary	**Robbery**	**Auto Theft**	**Theft from Auto**	**Burglary**	**Robbery**	**Auto Theft**	**Theft from Auto**
Local Attack	-0.0882***	0.0912	-0.361***	-0.113	-0.0346	-0.0139	-0.126***	-0.0596***
	(0.021)	(0.16)	(0.089)	(0.25)	(0.028)	(0.073)	(0.021)	(0.021)
Non-Local Attack	-0.0206***	-0.0188	-0.0134	-0.0349	-0.0400***	0.0170	-0.0288***	-0.0161**
	(0.0079)	(0.048)	(0.033)	(0.060)	(0.010)	(0.026)	(0.0090)	(0.0073)
	Rape	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**	**Rape**	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**
Local Attack	0.161	0.113	-0.202	-0.0493	0.197	0.149	-0.0598	0.134
	(0.13)	(0.17)	(0.14)	(0.15)	(0.17)	(0.24)	(0.090)	(0.17)
Non-Local Attack	-0.0789	-0.0874*	0.00122	-0.0148	0.0351	0.130	0.0256	0.0199
	(0.060)	(0.053)	(0.042)	(0.068)	(0.066)	(0.13)	(0.029)	(0.060)
	Murder	**Murder Acq.**	**Assault**	**Aggravated Assault**	**Murder**	**Murder Acq.**	**Assault**	**Aggravated Assault**
Local Attack	0.283	0.950**	-0.0564**	-0.254**	2.029***	2.017***	0.00408	-0.0502
	(0.29)	(0.47)	(0.024)	(0.099)	(0.15)	(0.34)	(0.020)	(0.079)
Non-Local Attack	-0.0591	0.0277	-0.00860	-0.0305	0.0610	-0.354	0.0148*	-0.00599
	(0.16)	(0.20)	(0.011)	(0.024)	(0.088)	(0.23)	(0.0085)	(0.031)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Table 8: Effect of a Large Terror Attack in the Last 5 Days on Crime by Type of Location, Israel 2000-2005

	Home				Public			
	Trespass	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**	**Trespass**	**Public Disorder**	**Disrupting Police**	**Disturbing Peace**
Local Attack	0.0389	-0.0491	-0.244	-0.144	0.0752	-0.00746	0.0839	-0.0727
	(0.17)	(0.084)	(0.21)	(0.35)	(0.065)	(0.062)	(0.056)	(0.15)
Non-Local Attack	0.122*	0.0117	0.112	-0.0224	0.0573***	0.0208	0.0382	0.0830
	(0.072)	(0.024)	(0.082)	(0.069)	(0.022)	(0.020)	(0.028)	(0.069)
	Burglary	**Robbery**	**Auto Theft**	**Theft from Auto**	**Burglary**	**Robbery**	**Auto Theft**	**Theft from Auto**
Local Attack	-0.0843**	0.0927	-0.663***	-0.567	-0.106***	0.122	-0.262***	-0.0805**
	(0.043)	(0.26)	(0.22)	(0.43)	(0.031)	(0.13)	(0.031)	(0.034)
Non-Local Attack	-0.0227*	-0.0452	-0.00876	-0.0440	-0.0344***	0.00483	-0.0351***	-0.0191*
	(0.012)	(0.084)	(0.046)	(0.10)	(0.013)	(0.038)	(0.011)	(0.010)
	Rape	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**	**Rape**	**Rape Acq.**	**Sexual Assault**	**Sexual Assault Acq.**
Local Attack	0.175	0.0156	-0.452	-0.354	-0.0106	0.0376	-0.145	-0.0467
	(0.22)	(0.24)	(0.29)	(0.29)	(0.27)	(0.42)	(0.12)	(0.23)
Non-Local Attack	-0.107	-0.149	-0.0457	0.00274	-0.0145	0.206	0.0475	-0.105
	(0.076)	(0.094)	(0.065)	(0.087)	(0.089)	(0.16)	(0.042)	(0.086)
	Murder	**Murder Acq.**	**Assault**	**Aggravated Assault**	**Murder**	**Murder Acq.**	**Assault**	**Aggravated Assault**
Local Attack	0.885*	2.558	-0.0937*	-0.175	1.736***	2.199***	0.0531	-0.213
	(0.49)	(8.52)	(0.051)	(0.16)	(0.20)	(0.50)	(0.039)	(0.15)
Non-Local Attack	-0.0253	0.0803	-0.0176	-0.0553	0.0947	0.175	0.00460	-0.00644
	(0.20)	(0.29)	(0.013)	(0.036)	(0.11)	(0.22)	(0.013)	(0.029)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Table 9: Effect of any Terror Attack in the Last 5 Days on Crime in Adjacent and Non-Adjacent Sub-districts

	Trespass	Public Disorder	Disrupting Police	Disturbing Peace	Burglary	Robbery	Auto Theft	Theft from Auto
Local Attack	0.0517**	-0.00850	0.0764	0.00217	-0.0677***	0.00209	-0.136***	-0.0601***
	(0.025)	(0.030)	(0.050)	(0.090)	(0.017)	(0.051)	(0.018)	(0.022)
Attack in Adjacent Subdistrict	0.0792***	0.00981	-0.000396	-0.0170	-0.0281***	0.0724*	-0.0560***	-0.0309***
	(0.027)	(0.024)	(0.027)	(0.059)	(0.011)	(0.041)	(0.013)	(0.011)
Attack in Non-Adjacent Subdistrict	0.0604***	-0.00938	0.0154	0.0509	-0.0258***	-0.00533	-0.0223**	-0.00588
	(0.018)	(0.013)	(0.020)	(0.044)	(0.0067)	(0.025)	(0.010)	(0.0088)

	Murder	Murder Acq.	Assault	Aggravated Assault	Rape	Rape Acq.	Sexual Assault	Sexual Assault Acq.
Local Attack	1.660***	1.692***	-0.0235	-0.142	0.176**	0.120	-0.103	0.0392
	(0.12)	(0.21)	(0.015)	(0.087)	(0.088)	(0.11)	(0.084)	(0.14)
Attack in Adjacent Subdistrict	0.00912	0.119	0.00101	-0.0284	-0.0501	0.0528	-0.0182	-0.0521
	(0.17)	(0.36)	(0.012)	(0.036)	(0.060)	(0.083)	(0.048)	(0.097)
Attack in Non-Adjacent Subdistrict	-0.0356	-0.262*	0.00493	-0.0173	-0.0234	-0.0534	0.0275	0.0428
	(0.084)	(0.16)	(0.0067)	(0.019)	(0.046)	(0.057)	(0.028)	(0.052)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Appendix Table A1: Results for Crimes of Public Behavior with Five Lags, Israel 2000-2005

	All Attacks				Large Attacks			
	Trespass	Public Disorder	Disrupt Police	Disturb Peace	Trespass	Public Disorder	Disrupt Police	Disturb Peace
0 Days Local	0.156***	0.0506	0.164***	0.0678	0.0821	0.0457	0.170*	-0.000354
	(0.056)	(0.083)	(0.056)	(0.23)	(0.082)	(0.15)	(0.097)	(0.44)
1 Day Local	0.114	-0.0108	0.0122	-0.119	0.205**	0.0291	0.0900	0.0267
	(0.083)	(0.071)	(0.079)	(0.21)	(0.10)	(0.17)	(0.11)	(0.25)
2 Days Local	0.108*	-0.00507	0.0419	-0.283	0.141	-0.123*	-0.0670	-0.0961
	(0.061)	(0.075)	(0.078)	(0.20)	(0.13)	(0.071)	(0.12)	(0.42)
3 Days Local	0.0127	0.0257	0.142**	0.209	0.0358	-0.0327	0.179	0.309
	(0.097)	(0.068)	(0.063)	(0.20)	(0.14)	(0.11)	(0.12)	(0.40)
4 Days Local	0.0252	-0.0675	0.0669	0.0832	0.111	-0.0159	0.0315	-0.0961
	(0.062)	(0.057)	(0.069)	(0.19)	(0.078)	(0.11)	(0.13)	(0.45)
5 Days Local	-0.107**	-0.000797	-0.0268	-0.0120	-0.0659	-0.0559	-0.125	-0.830
	(0.049)	(0.059)	(0.077)	(0.17)	(0.085)	(0.090)	(0.15)	(2.68)
0 Days Non-Local	0.0993***	0.0360*	0.0353	0.110**	0.129***	0.0224	0.0367	0.217**
	(0.021)	(0.020)	(0.024)	(0.049)	(0.038)	(0.036)	(0.038)	(0.100)
1 Day Non-Local	0.0964***	0.00735	0.0455*	0.0107	0.0995***	0.0509	0.107**	0.0639
	(0.021)	(0.017)	(0.027)	(0.058)	(0.036)	(0.032)	(0.043)	(0.10)
2 Days Non-Local	0.0144	-0.0354	-0.00747	0.0205	-0.0126	-0.0559*	0.0144	-0.100
	(0.024)	(0.022)	(0.031)	(0.073)	(0.042)	(0.032)	(0.040)	(0.098)
3 Days Non-Local	0.0501*	0.0455*	0.00182	0.0218	0.0807*	0.0347	0.00633	0.00869
	(0.030)	(0.025)	(0.029)	(0.055)	(0.048)	(0.037)	(0.055)	(0.11)
4 Days Non-Local	0.0413**	-0.0105	-0.0171	-0.0552	0.0341	0.0117	0.0436	-0.265***
	(0.020)	(0.019)	(0.027)	(0.075)	(0.048)	(0.031)	(0.041)	(0.094)
5 Days Non-Local	-0.00332	0.0203	0.0237	-0.0209	0.0116	0.00841	0.0528	0.0291
	(0.021)	(0.021)	(0.033)	(0.067)	(0.032)	(0.029)	(0.038)	(0.087)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Appendix Table A2: Results for Property Crimes with Five Lags, Israel 2000-2005

	All Attacks				Large Attacks			
	Burglary	Robbery	Auto Theft	Theft from Auto	Burglary	Robbery	Auto Theft	Theft from Auto
0 Days Local	-0.0886***	-0.0623	-0.161***	-0.0705**	-0.188***	0.148	-0.371***	-0.0648
	(0.033)	(0.16)	(0.048)	(0.031)	(0.052)	(0.20)	(0.100)	(0.054)
1 Day Local	-0.0632*	0.189	-0.140***	-0.0467	-0.0927	0.445*	-0.277***	-0.0518
	(0.034)	(0.17)	(0.044)	(0.037)	(0.067)	(0.25)	(0.078)	(0.070)
2 Days Local	-0.0202	0.117	-0.148***	-0.0612	0.0170	0.190	-0.301***	-0.136**
	(0.043)	(0.12)	(0.047)	(0.040)	(0.062)	(0.17)	(0.094)	(0.059)
3 Days Local	-0.0912***	-0.131	-0.138***	-0.0787**	-0.190***	-0.0576	-0.254***	-0.102
	(0.035)	(0.17)	(0.047)	(0.032)	(0.058)	(0.32)	(0.061)	(0.075)
4 Days Local	-0.0908***	-0.0164	-0.119***	-0.0674**	-0.141**	0.0148	-0.252***	-0.0441
	(0.033)	(0.17)	(0.043)	(0.033)	(0.055)	(0.24)	(0.068)	(0.047)
5 Days Local	-0.0350	-0.134	-0.0955**	-0.0472	0.0227	-0.107	-0.148**	-0.0856
	(0.037)	(0.16)	(0.044)	(0.034)	(0.057)	(0.26)	(0.062)	(0.068)
0 Days Non-Local	-0.0216**	-0.0107	-0.0158	-0.0172*	-0.000539	-0.0136	-0.0414**	-0.0215
	(0.010)	(0.043)	(0.016)	(0.0097)	(0.012)	(0.066)	(0.020)	(0.015)
1 Day Non-Local	-0.0380***	0.0955**	-0.0454***	-0.0144	-0.0674***	0.110	-0.0629***	-0.0328**
	(0.011)	(0.038)	(0.013)	(0.0098)	(0.015)	(0.075)	(0.022)	(0.016)
2 Days Non-Local	-0.0323***	-0.0182	-0.0494***	-0.0214**	-0.0254*	-0.0383	-0.0545**	-0.0255*
	(0.012)	(0.037)	(0.014)	(0.0099)	(0.015)	(0.074)	(0.022)	(0.015)
3 Days Non-Local	-0.0121	0.0147	-0.0397***	0.00142	-0.0240	-0.00357	-0.0210	0.00876
	(0.011)	(0.049)	(0.013)	(0.0080)	(0.015)	(0.066)	(0.020)	(0.014)
4 Days Non-Local	-0.0147	0.0464	-0.0311**	-0.00764	-0.00698	-0.0347	-0.0219	-0.0115
	(0.0090)	(0.047)	(0.013)	(0.010)	(0.013)	(0.067)	(0.017)	(0.018)
5 Days Non-Local	-0.0349***	-0.0223	-0.00640	-0.00420	-0.0339**	-0.00972	-0.00502	-0.00826
	(0.0079)	(0.047)	(0.014)	(0.011)	(0.016)	(0.069)	(0.024)	(0.016)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Appendix Table A3: Results for Sexual Crimes with Five Lags, Israel 2000-2005

	All Attacks				Large Attacks			
	Rape	Rape Acq.	Sexual Assault	Sexual Assault Acq.	Rape	Rape Acq.	Sexual Assault	Sexual Assault Acq.
0 Days Local	0.161	0.135	-0.143	-0.0263	0.463	0.382	-0.203	-0.511
	(0.27)	(0.32)	(0.19)	(0.27)	(0.28)	(1.98)	(0.20)	(2.13)
1 Day Local	-0.606**	-0.339	0.0240	0.129	-0.619	-0.709	-0.105	0.165
	(0.28)	(0.33)	(0.17)	(0.25)	(1.98)	(4.15)	(0.33)	(0.56)
2 Days Local	0.0858	0.399*	-0.0660	0.284	-0.0175	0.251	-0.695**	-0.273
	(0.21)	(0.21)	(0.16)	(0.33)	(0.38)	(0.48)	(0.33)	(0.50)
3 Days Local	0.503**	0.538**	0.131	0.104	0.153	0.307	0.0605	-0.0959
	(0.22)	(0.26)	(0.11)	(0.15)	(0.29)	(2.17)	(0.22)	(0.51)
4 Days Local	0.446**	0.0520	-0.259*	0.00998	0.268	0.0976	-0.208	-0.182
	(0.18)	(0.37)	(0.16)	(0.24)	(0.35)	(2.94)	(0.31)	(0.38)
5 Days Local	0.127	-0.249	-0.347**	-0.432	0.152	-0.178	-0.310	-0.659
	(0.24)	(0.43)	(0.15)	(0.36)	(0.31)	(2.80)	(0.23)	(0.69)
0 Days Non-Local	0.0767	0.0984	0.0737*	0.142	0.0723	0.0913	0.140*	0.0905
	(0.072)	(0.10)	(0.041)	(0.090)	(0.14)	(0.15)	(0.078)	(0.14)
1 Day Non-Local	-0.170*	-0.165	-0.0252	-0.0601	-0.0751	0.0190	0.0458	0.0166
	(0.087)	(0.10)	(0.042)	(0.064)	(0.13)	(0.18)	(0.060)	(0.12)
2 Days Non-Local	-0.0660	-0.0243	-0.100**	-0.0751	-0.388**	-0.238	-0.205***	-0.313**
	(0.070)	(0.13)	(0.041)	(0.083)	(0.16)	(0.22)	(0.077)	(0.14)
3 Days Non-Local	0.0836	0.0479	0.116**	0.103	-0.0904	-0.195	0.0106	-0.0389
	(0.077)	(0.11)	(0.052)	(0.074)	(0.14)	(0.14)	(0.067)	(0.12)
4 Days Non-Local	0.0152	-0.0670	0.0210	-0.0284	0.00892	0.00869	0.117**	0.00687
	(0.077)	(0.087)	(0.050)	(0.093)	(0.12)	(0.17)	(0.057)	(0.13)
5 Days Non-Local	0.00806	0.0267	0.0449	0.157*	0.00790	-0.0951	-0.0173	0.0107
	(0.082)	(0.10)	(0.046)	(0.081)	(0.12)	(0.19)	(0.060)	(0.11)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Appendix Table A4: Results for Violent Crimes with Five Lags, Israel 2000-2005

	All Attacks				Large Attacks			
	Murder	Murder Acq.	Assault	Aggravated Assault	Murder	Murder Acq.	Assault	Aggravated Assault
0 Days Local	3.371***	3.394***	-0.0275	-0.126	3.180***	3.754***	-0.0496	-0.201
	(0.12)	(0.30)	(0.035)	(0.11)	(0.19)	(0.36)	(0.095)	(0.20)
1 Day Local	0.294	-0.00530	-0.0592*	-0.271**	0.445	0.435	-0.0483	-0.565**
	(0.38)	(4.29)	(0.034)	(0.14)	(0.43)	(5.09)	(0.058)	(0.27)
2 Days Local	-0.822	-12.96***	-0.0376	-0.0607	-16.20***	-11.99***	-0.106**	-0.610
	(4.19)	(1.84)	(0.049)	(0.15)	(1.03)	(2.47)	(0.052)	(0.37)
3 Days Local	-0.416	0.421	0.0287	-0.135	-0.589	0.803	0.0187	0.107
	(2.16)	(0.54)	(0.029)	(0.14)	(7.00)	(7.99)	(0.041)	(0.21)
4 Days Local	-0.234	-0.251	-0.00808	-0.0433	0.435	0.659	0.0394	-0.170
	(2.16)	(7.51)	(0.039)	(0.15)	(2.18)	(7.90)	(0.052)	(0.26)
5 Days Local	0.207	0.298	-0.0162	-0.147	0.0732	0.690	0.0126	0.0341
	(0.44)	(2.27)	(0.033)	(0.12)	(4.32)	(7.82)	(0.056)	(0.20)
0 Days Non-Local	0.295**	0.0972	0.0151*	-0.0699*	0.100	0.191	-0.0132	-0.0596
	(0.15)	(0.21)	(0.0092)	(0.040)	(0.27)	(0.37)	(0.021)	(0.058)
1 Day Non-Local	0.0788	-0.238	-0.00794	-0.0450	0.0584	-0.631	-0.00768	-0.105*
	(0.11)	(0.35)	(0.014)	(0.035)	(0.21)	(2.05)	(0.018)	(0.054)
2 Days Non-Local	-0.0844	-0.271	-0.00789	0.00948	-0.315	-0.311	-0.0256**	-0.0362
	(0.11)	(0.27)	(0.012)	(0.042)	(0.24)	(0.46)	(0.013)	(0.052)
3 Days Non-Local	-0.129	0.305	0.00673	-0.00478	0.380*	0.854***	0.00401	-0.0176
	(0.12)	(0.19)	(0.012)	(0.035)	(0.21)	(0.26)	(0.016)	(0.053)
4 Days Non-Local	-0.0842	-0.410	-0.00151	-0.0103	-0.0287	-0.168	-0.00257	-0.0274
	(0.15)	(0.30)	(0.013)	(0.036)	(0.23)	(0.44)	(0.015)	(0.070)
5 Days Non-Local	0.0586	-0.184	0.0133	-0.0886**	0.109	0.201	0.0104	-0.00434
	(0.16)	(0.31)	(0.0095)	(0.039)	(0.19)	(0.39)	(0.016)	(0.063)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each subdistrict-year-month, dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.

Appendix Table A5: Effect of Terror in the Last 5 Days on Crime by Size of Attack, by District Level

	All Fatal Attacks				Large Attacks			
	Trespass	Public Disorder	Disrupting Police	Disturbing Peace	Trespass	Public Disorder	Disrupting Police	Disturbing Peace
Local Attack	0.0535*	-0.0129	0.0484	-0.0551	0.0644*	-0.0258	0.0665	-0.113
	(0.030)	(0.024)	(0.033)	(0.077)	(0.036)	(0.034)	(0.044)	(0.16)
Non-Local Attack	0.0730***	-0.00366	0.0160	0.0309	0.0608***	0.0194	0.0420*	0.0325
	(0.016)	(0.016)	(0.017)	(0.035)	(0.022)	(0.020)	(0.025)	(0.054)
	Burglary	Robbery	Auto Theft	Theft from Auto	Burglary	Robbery	Auto Theft	Theft from Auto
Local Attack	-0.0564***	0.0525	-0.104***	-0.0452***	-0.0674***	0.0691	-0.180***	-0.0719**
	(0.011)	(0.047)	(0.017)	(0.013)	(0.022)	(0.10)	(0.029)	(0.028)
Non-Local Attack	-0.0253***	0.00875	-0.0247***	-0.0141*	-0.0267***	-0.00264	-0.0304**	-0.0164
	(0.0084)	(0.028)	(0.0080)	(0.0074)	(0.0077)	(0.036)	(0.014)	(0.011)
	Rape	Rape Acq.	Sexual Assault	Sexual Assault Acq.	Rape	Rape Acq.	Sexual Assault	Sexual Assault Acq.
Local Attack	0.0687	0.129	-0.0660	0.0336	0.0719	0.0864	-0.229**	-0.145
	(0.080)	(0.12)	(0.057)	(0.089)	(0.16)	(0.17)	(0.10)	(0.18)
Non-Local Attack	-0.0319	-0.0569	0.0212	0.00254	-0.0876	-0.0969	0.0342	-0.0434
	(0.048)	(0.054)	(0.035)	(0.066)	(0.065)	(0.10)	(0.039)	(0.075)
	Murder	Murder Acq.	Assault	Aggravated Assault	Murder	Murder Acq.	Assault	Aggravated Assault
Local Attack	1.113***	1.227***	0.000243	-0.0516	1.202***	1.955***	-0.0147	-0.150**
	(0.089)	(0.19)	(0.012)	(0.035)	(0.15)	(0.31)	(0.025)	(0.073)
Non-Local Attack	-0.00347	-0.189	0.00349	-0.0211	0.00936	0.0215	-0.00405	-0.0302
	(0.076)	(0.14)	(0.0072)	(0.020)	(0.088)	(0.22)	(0.0088)	(0.033)

Notes: Standard errors are in parentheses. *** indicates significance at 1%; ** indicates significance at 5%; and * indicates significance at 10%. Each coefficient comes from a Poisson regression which includes a fixed-effect for each district-year-month (six districts), dummy variables for day of the week, and a dummy variable for holidays. "All attacks" consider any attack with at least one fatality as a terror attack, while "large attacks" consider only attacks with at least five casualties. Standard errors are clustered by level of the fixed-effect.