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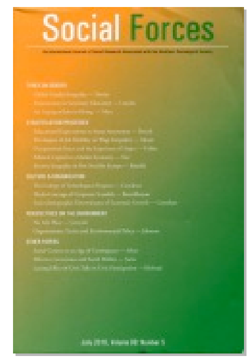

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Societal Responses to Endemic Terror: Evidence from Driving Behavior in Israel

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In this article, using data on traffic volume and fatal accident rates in Israel from 2001 to 2004 – a period spanning much of the Second Intifada – we examine the population-level responses to endemic terror to uncover whether societies become habituated so that the response weakens following repeated attacks or whether they become increasingly sensitized so subsequent attacks have a greater impact. Our analysis, using distributed-lag time series models, supports earlier findings while highlighting the persistence of the response to terror attacks even several years into the violence. There are, however, signs that the reaction to terror has accelerated. This shift, which is not naturally seen as evidence for either habituation or sensitization, is suggestive of social learning of norms over time.

Introduction

There has been a dramatic increase in studies focusing on the implications of terror following the September 11th attacks. Far-ranging consequences have been shown to result from such one-time attacks – from rises in population-level measures of stress and anxiety (Schlenger et al. 2002; Schuster et al. 2001; Verger et al. 2004), to increased drinking and smoking (Vlahov et al. 2002, 2004), and deterioration in observable health outcomes such as cardiovascular disorders (Feng et al. 2006; Steinberg et al. 2004). A broader set of studies, often focusing on Israel, have also detailed the broader macroeconomic (Eckstein and Tsiddon 2004; Eldor and Melnick 2004), political (Berrebi and Klor 2006; Gould and Klor forthcoming) and behavioral (Stecklov and Goldstein 2004) implications of terror. Do repeated attacks cause societies to adapt and become habituated or do they sensitize populations and cause them to become increasingly traumatized? Understanding the evolution of the social response to terror may provide insights into the ability of societies to deal with repeated stress, not just terrorist attacks and war, but also natural disasters and other large-scale crises.

The question of how societies respond to repeated terror attacks requires both an understanding of how stress might be produced as well as the mechanisms through which this response might weaken or strengthen over time. Our ap-

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proach builds on both micro- and macro-level explanations relating adaptations to stress. At the individual level, an extensive literature in psychology examines individual reactions and adaptations to terrorist attacks, war and disasters. This includes the exposure of civilians to wartime bombings (Bleich et al. 1992; U.S. Strategic Bombing Survey 1947), how populations are affected by terror and natural disasters (North and Pfefferbaum 2002; Tierney et al. 2006), as well as studies that analyze the reactions of soldiers to extended periods of combat (Friedman 2006; Hoge et al. 2006). At the macro level, communities, societies and state institutions may adapt, and their reaction may be critical in determining response in the face of political violence (Collins 2004; Kimmerling 1985) or natural or man-made disasters (Erikson 1976; Quarantelli and Dynes 1977; Rodriguez et al. 2006).

The focus of our investigation is Israel, where we examine the social response to repeated terrorist attacks over a four-year period during the Second Intifada– from Jan. 1, 2001 to Dec. 31, 2004. We employ unique data on driving behavior and traffic accidents within Israel over this period as well as on the timing of terrorist attacks. Our research seeks to determine whether past findings that demonstrated a link between terrorism and driving for an 18-month period continue to hold when the length of the study period is extended to four years. A second aim is to use the extended time series on terror, traffic volume and traffic fatalities to test whether the response to terror shifts over time.

Measuring the Response to Terror

Early perspectives on the social consequences of terrorism were often based on studies of population-level responses to disasters and wars (National Research Council 2003; Tierney 2007). Unfortunately, much of that evidence was hearsay and after-the-fact reports, often from participants, and "subject to selectivity and distortion."(National Research Council 2003; Tierney et al. 2006) More recently, a large number of systematic studies on the societal reaction to terror have been carried out using better-designed surveys and based on random-sampling methods. Many of these studies are based on surveys carried out immediately after the event, and generally include instruments to test for PTSD or other forms of stress and anxiety. These studies have been valuable in providing insight into the emotional stress following events such as the 9/11 attacks or terror attacks in Israel or Spain, and they have enabled researchers to distinguish those individual-level characteristics more associated with severe responses to terrorism. However, even in the best of cases, there is a delay of 3 to 5 days from the attack to the start of data collection, and in most cases the delay is longer. The delay exacerbates the possibility that individual responses to traumatic events will be socialized through friends or media sources (Tierney et al. 2006). Furthermore, the potential implications of non-response bias in surveys are very difficult to gauge following disasters or terrorist attacks (North and Pfefferbaum 2002; Silver et al. 2002).

An alternative approach is to focus on behavioral changes that follow population-level traumatic events. In this respect, both data on the amount people drive (traffic volume) and on the quality of their driving (traffic accidents) provide important instruments for measuring the behavioral response to terrorism. First, the lack of selectivity of driving in a society, which is highly mobilized like Israel, widens the generalizability of the response. Another advantage is that traffic accident and volume data are collected in routine data systems with fine precision, offering a method to gauge the behavior before and after the event studied. Also, the routine data systems in place for collection of traffic accident and traffic volume are not systematically affected by terror attacks themselves helping to assure that causality is correctly identified.

The two outcomes in our analysis–traffic volume and fatal traffic accidents–each offer distinct insight into the effect of terror on a different socio-behavioral process. Traffic volume, which measures the number of cars on the road, is in part a measure of discretionary travel. Changes in this indicator can capture the impact of a terrorist attack on people's inclination or desire to undertake leisure activities, or their response to social signals that staying home is "correct" and "safe" following an attack. The decline in leisure is consistent with evidence indicating short-term falls in coffee shop sales in Jerusalem immediately following attacks in Israel (Spilerman and Stecklov 2009). Increasing use of roadblocks following a terrorist attack, a common practice, is also relatively short-term and generally limited to the broader vicinity of the attack (Weisburd et al. 2009). In addition, changes in traffic volume could be further affected by changes in work-related traffic if substitutions occur between private automobile driving and alternative forms of transportation such as busses, which may face higher perceived risks from terror–particularly following attacks that specifically targeted busses (Becker and Rubinstein 2010).

The traffic accident data measure the quality of driving for those who have made the decision to be on the road. In this case, the mechanism of influence on accidents is more likely associated with micro-behavioral change associated with stress and anxiety following terrorist attacks. There is a well-documented positive association between psycho-social stress and traffic accidents (Norris et al. 2000; Selzer et al. 1968). This link is believed to be due to the association between driving behavior and aggression, stress and frustration (Norris et al. 2000; Shinar 1998; Underwood et al. 1999). Longitudinal studies on war veterans provide further evidence of this link between stress and driving behavior. They show that war veterans, experiencing greater levels of stress following war-time experiences, also face higher risks of traffic mortality (Macfarlane et al. 2000; Writer et al. 1996).

The link between stress and fatal traffic accidents has also been discussed in the literature on imitative suicides. A series of seminal studies has shown that suicides, traffic fatalities and airplane accidents often increase following well-publicized suicides and murders (Bollen and Phillips 1982; Phillips 1977, 1978, 1979), suggesting that some portion of traffic fatalities are in fact disguised suicides (Phillips

1977; Ohberg 1997). Thus, terrorist attacks, particularly given the widespread and graphic television attention they receive, may lead to more covert suicides in the form of traffic fatalities (Stecklov and Goldstein 2004).

The current study builds directly on prior research showing the response of driving behavior in the wake of terrorist attacks (Stecklov and Goldstein 2004). In the United States, following 9/11, people shifted modes of long distance travel away from airplanes, and this choice has been connected to an increase in total fatalities associated with travel (Blalock et al. 2008). In Israel, relatively small distances mean that domestic travel is almost entirely by surface transportation. Prior research in Israel has shown that the amount people drive is reduced in the short term following terrorist attacks, but this effect is delayed by a day or two following the attack (Stecklov and Goldstein 2004). Also, fatal traffic accident rates appear to rise following terrorist attacks, although this substantial and significant increase is only observed after a three-day lag and then quickly dissipates (Stecklov and Goldstein 2004).

Habituation or Sensitization to Endemic Terror?

Several studies based on single-event terrorist attacks have shown that effects weaken over time (Silver et al. 2002; Vlahov et al. 2004). Yet, when a society such as Israel or Iraq faces a form of trauma that is repeated many times over an extended period of time, another fundamental question arises. How does the population-level response to terror evolve through the repeated experience of this same form of traumatic event?

We consider two alternative perspectives for understanding how the effect of terrorism may shift over time–assuming an effect is identified. One is that the population's reaction weakens after each attack as individuals become habituated. The other is that sensitivity to terrorism increases as the result of repeated assaults. Understanding how this process evolves offers a unique lens into individual and social processes of adaptation.

At the micro level, the process of habituation is well understood in both human and non-human organisms, although there is debate about the underlying mechanisms that drive the process. Both psychological and physiological research on habituation demonstrate how the response to a repeated stimuli may be modified by adaptive learning (del Rosal et al. 2006; Thompson and Spencer 1966; Thompson 1986). Furthermore, empirical evidence suggests that individuals tend to overreact to threats that are rare and unfamiliar such as the risk of flying (Blalock et al. 2008; Sivak and Flannagan 2003; Sunstein 2003). Increased familiarity with the "risk" of terror may be instrumental in reducing the reaction to terrorism. Thus, terror at the early stages will invoke stronger fears and responses within the population, but less fear will be generated by later attacks as the threat and risk become increasingly familiar.

Habituation may also occur simultaneously at the broader group or societal level. Within emergent norm theory, collective behavior is altered as crises force the reevaluation of what is legitimate conduct (Turner and Killian 1987). Furthermore, an increasing consensus of what the social normative response to terrorism may be can cause habituation as individuals receive "psychological gain" from a narrowing set of behavioral choices (Berger and Luckmann 1966). Individuals can then adapt their leisure responses to fall within the range of legitimate behavior– whether this behavior involves dating, coffee breaks or other leisure activities.

Habituation is also facilitated by the complex institutional structures that connect individuals. Because terrorism targets entire societies, societal institutions such as family, kin, community and state may play an increasingly active and effective role and contribute to a shift in the response to terror over time. This may be a direct result of families learning to better identify and support more sensitive family members (Bleich et al. 2003; Kaitz et al. 2008; Shalev et al. 2006). New organizational and institutional forms may also emerge to provide necessary assistance and enable individuals to cope better with the ongoing threat (Kimmerling 1985; Stadler et al. 2005). Becker and Rubinstein (2010) use natural variation in media exposure in Israel– a product of the non-publication of Saturday newspapers– to show that media coverage plays an important role in the social response to terrorist attacks (Becker and Rubinstein 2010). Then, coping may be further facilitated over time if media attention declines during endemic terror– a pattern which appears to have occurred in Israel (Frosh and Wolfsfeld 2007; Liebes and Kampf 2007).

In contrast to habituation, the reaction to terrorism may strengthen rather than dissipate as attacks are repeated, leading to increased sensitivity over time. Heightened sensitivity, like habituation, is a form of response to repeated stimuli (Kandel 1976; Thompson 1986). After a particular fear is triggered in a person, a subsequent reoccurrence may stimulate a stronger response because of the development of "hyper-excitable fear circuits."(Rosen and Schulkin 1998) Thus, early terrorist attacks may cause a relatively weak reaction, but hard-wire an individual so that later attacks generate a stronger response. Furthermore, as casualty counts rise, increasing numbers of people become linked through family or friendship to dead or injured victims, potentially contributing to an increase in response to terrorist attacks.

At the broader macro level there is little reason to expect institutional mechanisms to strengthen responses over time. In this sense, the impact of terrorism is quite different than that of war, given that most institutions continue to function in some capacity. In war, governments may collapse, providing little or no support as occurred in late 20th century Liberia (Levitt 2005). In the case of Israel, however, Kimmerling (1985) argues that past wars prepared Israel's central institutions, for the most part, to deal effectively with conflict.

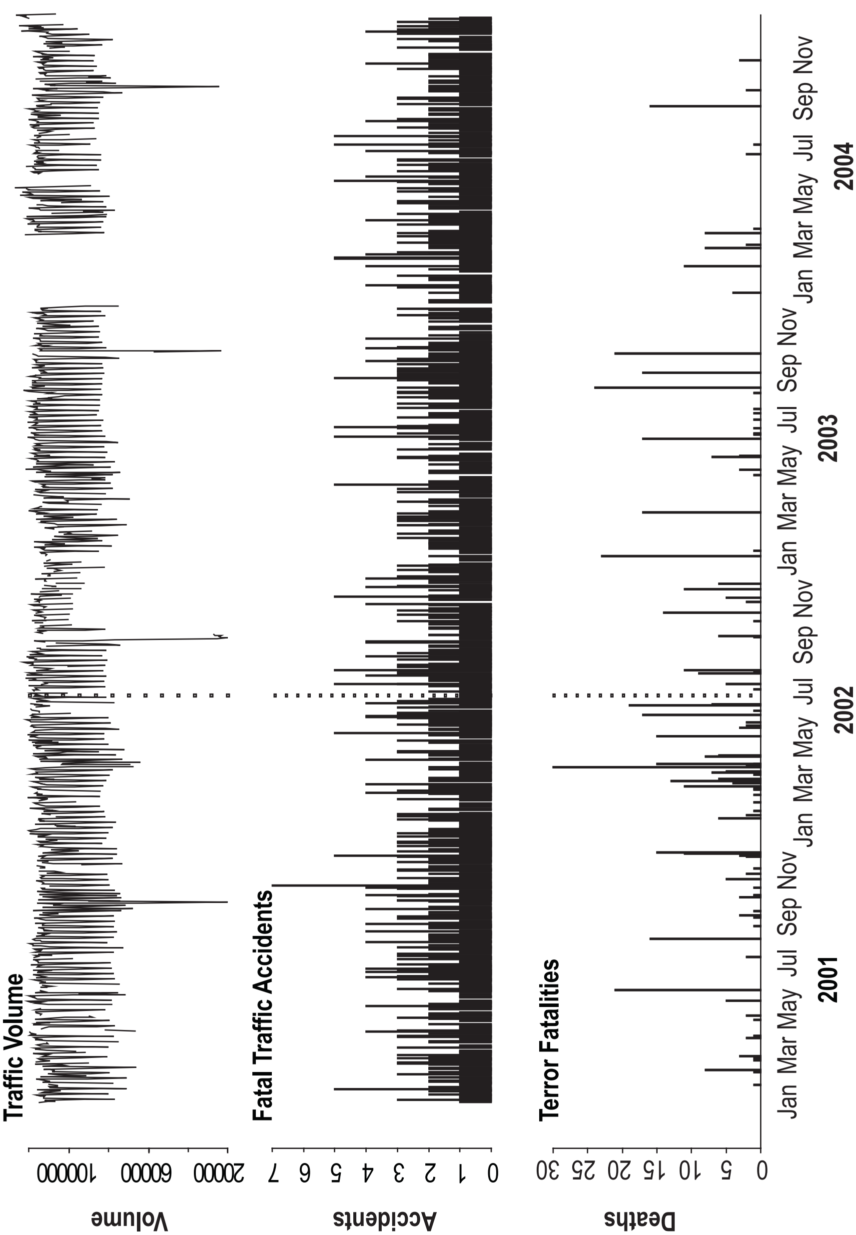
Ultimately, whether habituation or sensitization dominates, or whether they cancel out, the result is informative for understanding the connection between social stress and behavior. On the one hand, micro-level theory provides no clear prediction while sociological reasoning is less ambiguous and would tend to favor habituation. Of course, both the micro- and macro-level processes must work jointly further complicating any prediction.

Data Sources and Methods of Analysis

Data Sources

Our analysis is based on a combination of continuous, routinely collected data on automobile traffic volume levels and fatal traffic accidents, which enable us to gauge the population-level reaction to terrorist attacks and shifts in this reaction over time. Equally important, because such a large proportion of the population

Figure 1. Daily Traffic Volume, Fatal Accidents and Terrorist Fatalities



drives, our indicator has excellent population level coverage. Traffic accident data provide our second indicator for the population reaction to terrorism. We excluded data on non-fatal accidents for reliability concerns (Elvik and Mysen 1999; Hauer and Hakkert 1988), and considered only data from fatal traffic accidents.

Traffic volume data provide exceptionally precise feedback into the response of the population to terrorism. Do attacks cause people to be less mobile, less outgoing and to reduce their activities in order to lessen their exposure? Fatal traffic accident data, in combination with traffic volume data, produce traffic accident rate measures, which may uniquely identify the extent to which drivers are stressed and aggressive. Both sources of data are routine, continuous systems which alleviates the possibility of psychosocial response biases produced by surveys following violent events (Dijkema et al. 2005; Norris et al. 2002). The pseudo nature of the fatal accident rate we use is due to the fact that fatal accidents occur throughout the country, while the exposure indicator is based on a single freeway in central Israel. However, it should be noted that the Ayalon freeway in Israel is Israel's most travelled freeway and bisects its largest city, Tel Aviv (Bar-Gera 2007).

Our earlier work has identified some potentially important population-level reactions to terrorism using these data (Stecklov and Goldstein 2004). Large and significant declines in traffic following terrorist attacks have been identified using data from the first 18 months of the Second Intifada (Jan. 1, 2001 to June 22, 2002). These declines are centered on the third day after the attacks. Data on traffic accident rates, calculated from the number of fatal traffic accidents nationwide on day *t,* corrected for exposure levels based on traffic volume data for the Ayalon on day *t*, showed a short-lived decline in light accident rates and no obvious pattern in serious accident rates following terrorist attacks. However, both types of accident data are suspect because of potential reporting biases (O'Day 1993). In fact, fatal accident data, which suffer a much smaller degree of inaccuracy (Elvik and Mysen 1999), showed that the fatal accident rate rose dramatically on the third day following attacks. This large and significant rise of almost 35 percent ($p = .01$) shows an even greater effect of 69 percent ($p = .02$) when only large terrorist attacks are included.

Data on traffic volume is routinely collected using rubber gauges placed at various points along the freeway. The gauges provide a continuous relay of traffic flow data, collected in a central database and aggregated into counts for each five-minute interval. For our purposes, traffic volume is measured as the number of vehicles passing each of four points along this freeway. The values from the four locations are averaged to create a summary measure of average traffic flow for each

Note: Daily Traffic Volume Levels from Ayalon Freeway, Fatal Traffic Accidents from Israel Central Bureau of Statistics and Terrorist Attack Fatalities for Israel, Jan. 1, 2001 to Dec. 31, 2004 (with gaps).

five-minute interval, then the data are further aggregated into peak-hour and non-peak-hour averages. Further analysis showed little substantive difference between the peak and non-peak patterns in our data, leading us to combine the traffic volume into total daily averages (see Figure 1). The traffic volume data are also used to proxy for nation-wide driving exposure, enabling us to construct pseudo fatal traffic accident rates for the country as a whole (see Figure 1).[1]

Data on terrorist attacks are obtained from the International Policy Institute for Counter-Terrorism at the Interdisciplinary Center of Herziliya, Israel and B'tselem, a human rights group. We only include attacks and traffic information from within the 1967 borders of Israel, given the substantial differences in population composition and infrastructure separating Israel proper and the settlements, so West Bank, Gaza and East Jerusalem are excluded. During the period covered by our analysis, 91 terrorist attacks are reported with at least one civilian fatality. These attacks produced a total of 505 victims for an average of 5.5 fatalities per fatal attack. In this analysis we distinguish large attacks as those with 10 or more fatalities, of which there were a total of 19.

We include a number of controls to capture the impact of various factors that might otherwise cause us to mistakenly determine a causal effect of terrorism. For example, if traffic volume tends to be higher on Sundays and attacks are more common on Sundays, then we might conclude an association between terrorism and traffic volume even though this connection is spurious. The controls we include are year, month of the year and day of the week for our daily observations of traffic accident volume as well as important holidays.

The current analysis extends the earlier study by supplementing the original data from the period Jan. 1, 2001 to Jun. 22, 2002 (Period 1) with new data to extend the analysis from June 23, 2002 to Dec. 31, 2004 (Period 2). However, several gaps exist during which traffic volume data were not collected (see top panel of Figure 1). These gaps are due to computer problems and not associated with terror.[2] In our final analysis, only days with a full 24 hours of data were used to avoid introducing additional error into the analysis. Our final data include 1,306 days over the four-year period. The daily average count of volume over this period was 105,729 vehicles per day (sd = 15,342). The most visible outliers in the top panel of Figure 1 are for Yom Kipper – the holiest day in the Jewish calendar and a day in which traffic volume is nearly six standard deviations below the mean. With respect to fatal accidents, there is an average of 1.2 per day (sd = 1.1).

Method of Analysis

Our statistical analysis is based on the use of regression methods to assess how traffic volume and fatal traffic accident rates are affected by terrorist attacks on the same day and any of the five subsequent days. We use a simple distributed-lag formulation whereby the effect of an event on each of the lagged days is separately estimated in the same model. While multiple lags may introduce high degrees of collinearity, preliminary analyses indicate low correlations between lagged days.[3] Prior analysis has already shown that five lagged days following the day of the attack is sufficient to capture the short-term dynamics following terrorist attacks (Stecklov and Goldstein 2004). Also, by keeping the length of the lags limited to five days following attacks, we reduce complications that result from overlapping intervals with multiple attacks.

Our analysis is based on both ordinary least squares regression and Poisson regression. We use linear regression for the logged values of the volume data primarily because we expect traffic volume effects to be in proportional rather than absolute terms. The logarithmic transformation also helps to reduce the influence of outliers in the traffic data. The count nature of the fatal accident data along with their distribution suggests we use a count-data model. A variety of statistical models are available in such cases enabling us to overcome the distributional properties that may make linear regression unattractive (Long and Freese 2000). A central assumption of the Poisson model is that the mean and variance are equal. Failure of this condition is common and may lead researchers to alternatives such as the negative binomial model (Donner 2007). In our sample, the mean and variance both equal 1.2, providing no indication of overdispersion and supporting the Poisson model.

Our baseline models for estimating the effect of terror on traffic volume on day t, V_t, is shown in Equation 1 and is,

$$\log(V_t) = \alpha + \beta \cdot X_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} \tag{1}$$

Here, the vector X contains dummy variables for year, month, day of week, and if a day is a holiday. The corresponding β vector gives the coefficients, which we show in exponentiated form, that capture the impact of a specific category relative to the reference category. The α term is the intercept. Within the summation, the terror dummy variable takes the value "1" if there has been a fatal terror attack on a particular day t and "0" otherwise. Thus, the γ_k coefficients each capture the impact of a terror attack on a particular day, t-k, on the value of V_t.

A related model is estimated for traffic fatality data, but using Poisson regression, so the model takes the form,

$$\log(F_t) = \log(V_t) + \alpha + \beta \cdot X_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} \tag{2}$$

Here, the number of fatal accidents on day t, F_t, is estimated while controlling for exposure. In this case, the additional $\log(V_t)$ term acts as an "offset," where the parameter estimate of the offset is constrained to equal 1 (McCullough and Nelder 1989), so that the volume of traffic is taken into account when predicting traffic fatalities. We include in Equation 2 the same set of control variables and the same set of lagged dummies as in Equation 1. In both the volume and accident regressions, our results are presented in exponential form so that a null effect of a factor is given by a value near "1." Our results are thus interpreted in terms of the proportional change in traffic volume or the fatal traffic accident rate following an attack occurring *k* days earlier.

In addition to a set of analyses that focus on a main effect of terrorism, our attention is concentrated on two approaches for testing for habituation or sensitization in the behavioral response. The first, the period interaction approach, tests to see whether the relationship between fatal terrorist attacks and traffic changes over time. The second, the memory effect approach, evaluates whether the cumulative number of fatal attacks in past months influences the impact of attacks in recent days.

To test for a change in the effect in the effect of the lags over time we include a simple interaction term between the lagged terms and a dummy indicator for Period 2. In equations 3 and 4, the variable Z takes the value (0) for Period 1 and Z takes the value (1) for Period 2. While the two periods are not split in the middle, they are also reasonably balanced.[4] The formal model for traffic volume, V_t, including the same controls as before as well as a main effect for the Period indicator, Z_t, is:

$$\log(V_t) = \alpha + \beta \cdot X_t + \lambda \cdot Z_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} + \sum_{k=0}^{5} \delta_k \cdot Z_t \cdot terror_{t-k} \quad (3)$$

The model in the case of traffic fatalities is,

$$\log(F_t) = \log(V_t) + \alpha + \beta \cdot X_t + \lambda \cdot Z_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} + \sum_{k=0}^{5} \delta_k \cdot Z_t \cdot terror_{t-k} \quad (4)$$

Here, the coefficients, $\delta_{k,}$ in the period interaction approach in equations 3 and 4 provide a test of whether the effect of terror shifts over time.

We also test for habituation or sensitization using an alternative approach. This alternative focuses more on a direct form of adaptation associated with the level of past violence. It involves testing whether the effect of terrorism in the past few days is affected by the level of terror in the previous month(s). We explore previous month, two months earlier, three-months earlier, and four to six months earlier. The appropriate equations are,

$$\log(V_t) = \alpha + \beta \cdot X_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} + \theta \sum_{j=t-n}^{t-m} terror_j \quad (5)$$

Similarly, we test the Poisson model for fatalities using,

$$\log(F_t) = \log(V_t) + \alpha + \beta \cdot X_t + \sum_{k=0}^{5} \gamma_k \cdot terror_{t-k} + \theta \sum_{j=t-n}^{t-m} terror_j \quad (6)$$

Our approach is based on testing for a moderating variable(s) based on the aggregate number of terrorist attacks for a given period of time from $t - n$ to $t - m$ days prior. Thus, the new term in the summation reflects the aggregation of the number of fatal attacks from t – n days ago, where the smallest value of n is 6 and the largest is 90, to *m* days ago, where the values range from 30 to 180 days depending on the specification. Thus, we test a series of intervals including 6-30 days, 30-60 days, 60-90 days and 90-180 days. Each non-overlapping interval produces a separate model. For each model, however, only a single value of θ is produced. We also show the results of a model including all four intervals jointly. While the models in equations 5 and 6 are interesting, the statistical test for the moderator effect actually requires one additional step. When the main effect of terrorism in recent days is significant, we test a series of interactions between the lagged effects and the number of attacks over one or more months prior to determine whether the effect of a recent attack might be *moderated* by a previous attack. These alternative specifications are not shown but involve inclusion of an additional interaction between terror and the aggregate measures of past *terror* into the models shown in equations 5 and 6.

Our analyses generate a large number of coefficients given that the distributed-lag model produces a unique coefficient estimate, γ (or δ where appropriate), for each lagged day t. We take into account the comparisons created by the multiple-lag coefficients in each model by using the Bonferroni method to multiply the traditional P-values on the lagged effects (Abdi 2007; Bland and Altman 1995). We adopt the Bonferroni corrected significance level of $\alpha^* = \alpha/6 = .0167$ to create a 90 percent confidence region with a significance level of $\alpha = .10$. The null hypothesis is that the true effect at all lags is zero, with the alternative being two-sided. Both the OLS and Poisson regression models have coefficients that are asymptotically normal, and so the confidence intervals use +/– 2.39 standard errors, which covers the desired $1 - \alpha^* = .9833$ interval. The adjusted confidence intervals produced by this correction increase our confidence in the significant effects we observe.

Results

Traffic Volume

Our baseline model for daily traffic volume for the entire four-year period is shown in the first column of Table 1. This baseline model is similar to equations 1 and 2 except the terror lag dummies and coefficients in the summation term are not included in the model. The reference category for all our models is the year 2001, month of January, and day-of-week Saturday. The results of the baseline model illustrate the powerful role of the covariates on the logged value of daily traffic volume. Traffic volume increases from year to year over the four-year period, tends to be higher during the summer, and is unsurprisingly lowest on Saturdays and holidays when observant Jews avoid driving and many stores and restaurants are closed.

Changes in the effect of attacks on traffic volume gauge the disruptive effect of terror attacks on routine activities and also shed light on the timing of responses– a reflection on how people reorganize their activities to reduce their vulnerability. Over the four-year period we find, as seen in Figure 2 and Table 2, that terrorist attacks reduce traffic volume on the day of the attack and the subsequent three

Table 1: Baseline Proportional Effects for OLS Volume Models and Accident Fatality Rate Poisson Models

	Traffic Volume Regression	Fatal Accident Rate Regression
2002	.996	.966
	(.718)	(.602)
2003	**1.022**	.9
	(.039)	(.128)
2004	**1.039**	**.841**
	(.001)	**(.019)**
February	.998	1.094
	(.908)	(.532)
March	1.02	1.013
	(.297)	(.923)
April	1.005	1.069
	(.781)	(.626)
May	**1.042**	.937
	(.034)	(.642)
June	1.034	**1.386**
	(.080)	**(.011)**
July	**1.046**	1.127
	(.018)	(.363)
August	**1.041**	1.331
	(.036)	**(.025)**
September	**.897**	**1.308**
	(.000)	**(.042)**
October	.99	1.238
	(.614)	(.105)
November	1.007	.996
	(.725)	(.979)
December	1.024	1.304
	(.249)	(.055)
Holiday	**.702**	**1.643**
	(.000)	**(.004)**
Sunday	**1.423**	**.727**
	(.000)	**(.001)**
Monday	**1.401**	**.68**
	(.000)	**(.000)**
Tuesday	**1.417**	**.711**
	(.000)	**(.000)**
Wednesday	**1.406**	**.716**
	(.000)	**(.001)**
Thursday	**1.438**	**.78**
	(.000)	**(.008)**
Friday	**1.207**	.893
	(.000)	(.233)
Observations	1,306	1,306
R-squared	.512	
Chi-squared		62.234

Notes: Significant coefficients and p-values estimates (in parentheses) are in bold. Reference categories are 2001 for year, January for month, and Saturday for Day-of-Week.

days. However, only the coefficient on lag 2 is significant. Specifically, we find that terrorist attacks are associated with a roughly 4-5 percent decline in traffic volume on the second day following an attack. This effect, which is highly significant ($p < .01$), also remains significant after we apply the Bonferroni multiple comparison adjustment to the confidence intervals (see figures 2 and 3).

Additional evidence that traffic volume declines we see are indeed causal can be obtained by checking for a "dose-response" effect, with larger attacks causing greater declines in traffic volume. This effect is observed in Period 1, when attacks with 10 or more fatalities produce larger declines in traffic volume (Stecklov and Goldstein 2004). Here, looking at the entire four-year period, we see that the dose-response effect is also evident for lag 2 (top right panel of Figure 2) where the impact of large attacks produces a larger, and significant, decline in traffic volume.

Looking at each period separately and focusing on the test of habituation by examining the shift over time, we note a decline of roughly 3 percent on day 3 following attacks in Period 1 (the lag-4 coefficient is significant at traditional levels but not at the Bonferroni adjusted levels). In contrast, during Period 2, the impact appears more immediately after the attacks and is seen from lags 0-2, with a peak of 9 percent on day 2 following an attack; the coefficients that are significant using standard confidence intervals are also significant after the Bonferroni adjustments (see Figure 2). Statistically, while the lag 1 and lag 2 coefficients differ across periods and are significant at traditional levels they are not significantly different from Period 1 after the Bonferroni adjustments. Thus, one cannot reject the hypothesis that the terror effects on daily traffic volume on the same day or one day after an attack that are observed in Period 2 do not differ from those seen in Period 1. However, this same test is significant on day 2 after an attack. Furthermore, this shift in the effect of terror on traffic volume on lags 0-2 is jointly highly significant ($p = .001$).

The alternative approach (Equation 5) to look at adaptation focuses on whether the effects of terror in the days immediate following the attack are affected by the level of terror in prior months. The results of a test for a direct additive effect of past terror in addition to the effect of more recent terror are shown in Table 3. Results are presented for a model which includes only fatal terrorist attacks 6 to 30 days prior (i.e., short memory effects) while subsequent model also includes attacks two, three or six months earlier (i.e., long memory effects).

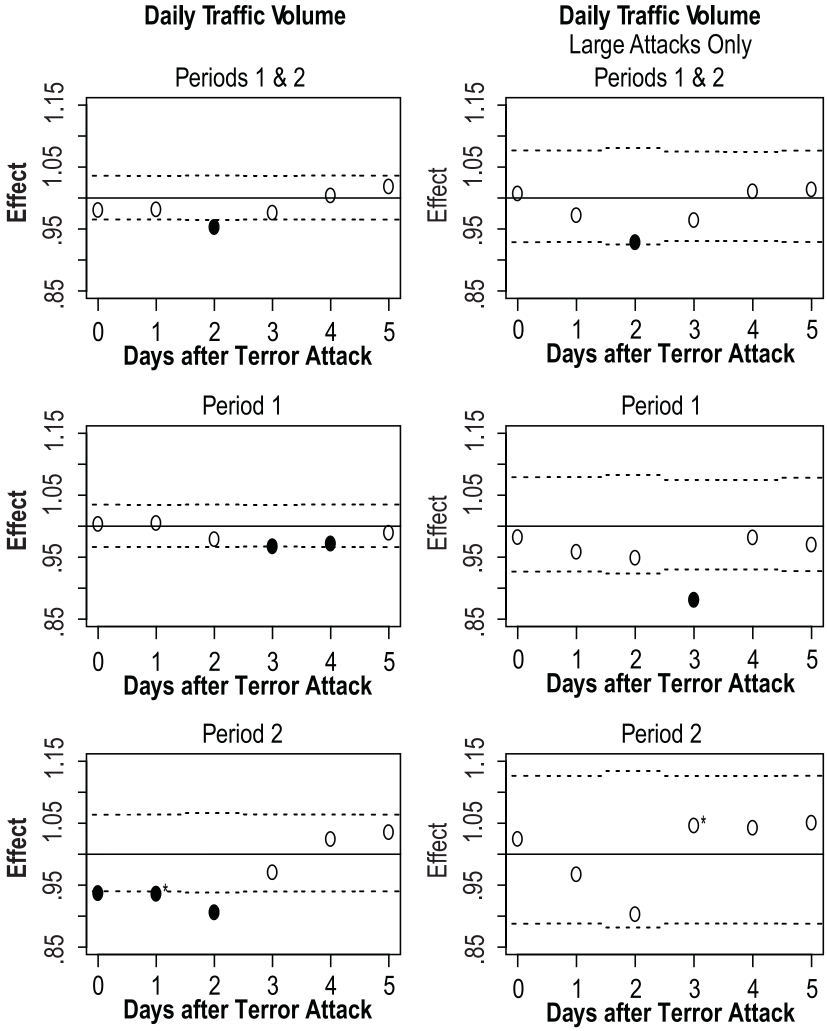
Results provide evidence that terrorist attacks in the six days before an attack also have an impact on traffic. Interestingly, the direct effect of terrorist attacks in previous months, where significant, is in the opposite direction. The days 6-30 measure comes out positive and significant ($p < .05$) for both all and large terrorist attack models indicating that past attacks, controlling for the negative effect of recent terrorism, are associated with higher traffic volume levels. We also introduce measures for the total number of fatal attacks two, three and four through six months earlier. The effect of the variables "Terror Days 6-30" remains positive and significant as is the effect of the variable "Terror Days 60-90." The

Table 2: Estimated Proportional Effects of Terror on Daily Traffic Volume

	Daily Traffic Volume							
	All Fatal Attacks				Large Attacks (>9 fatalities)			
Coefficient	Periods 1 & 2	Period 1	Period 2	Periods 1 & 2	Periods 1 & 2	Period 1	Period 2	Periods 1 & 2
Terror 0 Lag	.98	1.003	**.937**	1.005	1.007	.982	1.024	.974
	(.175)	(.829)	**(.011)**	(.783)	(.826)	(.566)	(.632)	(.556)
Terror 1 Lag	.981	1.005	**.936**	1.01	.972	.958	.967	.963
	(.196)	(.745)	**(.010)**	(.622)	(.354)	(.180)	(.501)	(.394)
Terror 2 Lag	**.953**	.979	**.906**	.977	**.928**	.949	.903	.948
	(.001)	(.128)	**(.000)**	(.227)	**(.022)**	(.114)	(.052)	(.249)
Terror 3 Lag	.976	**.967**	.97	.964	.964	**.881**	1.046	**.876**
	(.098)	**(.018)**	(.250)	(.059)	(.222)	**(.000)**	(.369)	**(.002)**
Terror 4 Lag	1.004	**.972**	1.024	.973	1.010	.981	1.042	.977
	(.807)	**(.045)**	(.360)	(.161)	(.732)	(.533)	(.407)	(.582)
Terror 5 Lag	1.018	.989	1.035	.993	1.013	.970	1.050	.976
	(.225)	(.438)	(.184)	(.710)	(.665)	(.330)	(.325)	(.560)
Period x Terror 0 Lag				**.933**				1.052
				(.019)				(.411)
Period x Terror 1 Lag				**.93**				1.004
				(.014)				(.951)
Period x Terror 2 Lag				**.933**				.950
				(.022)				(.429)
Period x Terror 3 Lag				1.012				**1.200**
				(.691)				**(.002)**
Period x Terror 4 Lag				1.057				1.070
				(.064)				(.257)
Period x Terror 5 Lag				1.046				1.075
				(.136)				(.242)
Observations	1,301	521	780	1,301	1,301	521	780	1,301
R-squared	.516	.685	.457	.527	.512	.692	.439	.519

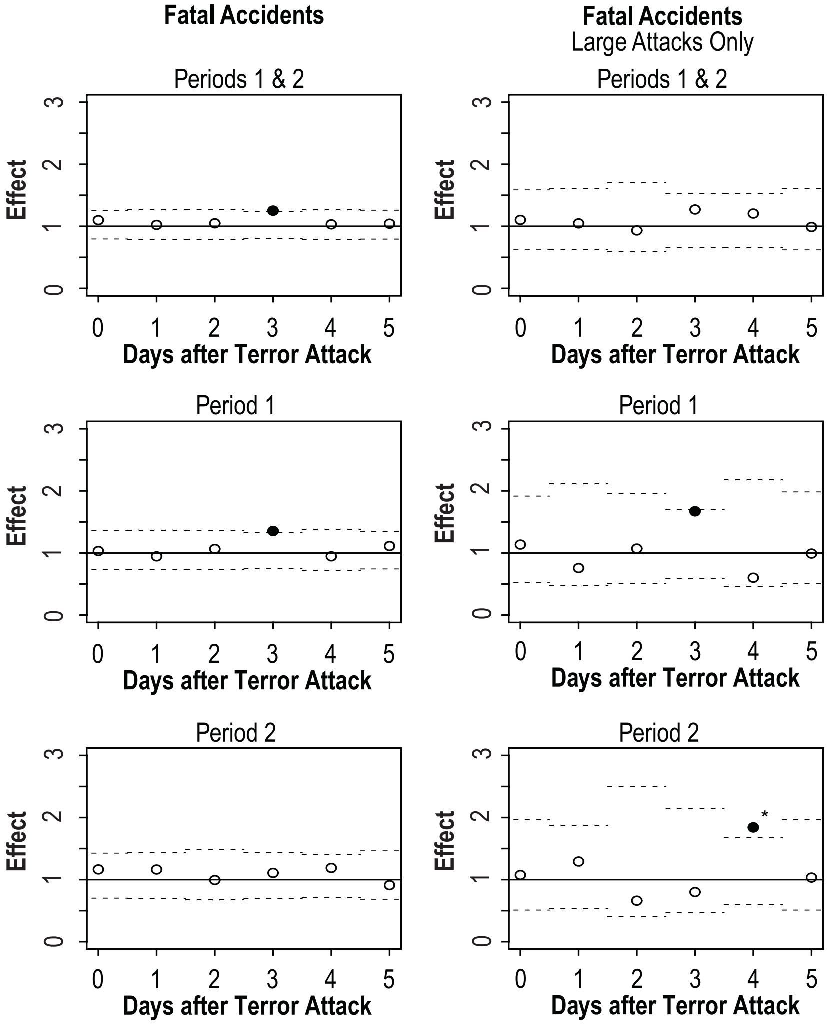
Notes: Significant effects and traditional p-values estimates (in parentheses) are in bold. Linear regression based on logged traffic volume variable. All models include controls seen in Table 1 including year, month of year, day of week and holiday.

Figure 2. Proportional OLS Estimates of Effects of Terror Attacks on Daily Traffic Volume for the Days Following Attacks



Notes: Data for Period 1, Period 2 and Periods 1 and 2, and for all attacks and large fatal attacks. We define "large" attacks as those in which 10 or more persons were killed. Effects that are not shaded are insignificant at the 5% level using traditional confidence intervals. Effects that are shaded are significant at the 5% level, without taking into account multiple comparisons. Effects outside of the dashed lines are significant at the 10% level, after accounting for six multiple comparisons, one for each lag. The * marks effects that differ significantly from Period 1 to Period 2 at the 10% level, after accounting for multiple comparisons.

Figure 3. Proportional Poisson Estimates of Effects of Terror Attacks on Daily Fatal Accident Rates for the Days Following Attacks



Notes: Data for Period 1, Period 2 and Periods 1 and 2, and for all attacks and large fatal attacks. We define "large" attacks as those in which 10 or more persons were killed. Effects that are not shaded are insignificant at the 5% level using traditional confidence intervals. Effects that are shaded are significant at the 5% level, without taking into account multiple comparisons. Effects outside of the dashed lines are significant at the 10% level, after accounting for six multiple comparisons, one for each lag. The * marks effects that differ significantly from period 1 to period 2 at the 10% level, after accounting for multiple comparisons.

other measures for terror in the past are not significant. The additive effect of past terror appears to depend on terror up to three months back and terror from earlier months generates no additional impact on traffic volume.

Are the effects we identified for terrorism over the past six days robust to the inclusion of controls for terrorism in previous months? The alternative is that the impact of terrorist attacks over the past few days depends on the level of terrorism in prior months. The results in Table 3 show that our main coefficient is unchanged (compare to Table 2) offering no evidence that the effect of attacks in the present is mediated by attacks in previous months. Furthermore, an interaction between the number of fatal attacks over the past month with the second-day lag effect is insignificant ($p = .88$) – furthering the claim of no shift in the impact of recent terror depending the scale of past terror.

Results of both tests suggest that the impact of terrorism on the amount people drive remains relatively stable as terror continues and there is little evidence of either habituation or sensitization. At the same time, results from the period interaction approach provide some evidence that the response accelerates in Period 2. This acceleration is indicated by a more rapid reaction as well as a speedier end of the effect. One possible explanation for such a shift in timing is that simple habituation or sensitization responses are insufficiently detailed to account for the complex dynamics when the response to terrorism is *learned* over time. In a manner reminiscent of Sherif's (1936) classic experiment using the autokinetic phenomenon, norms are learned through repeated exposure to the same event. The establishment of norms may in itself accelerate the response as well as facilitate the recovery. Thus, our results might indicate that a particular form of habituation is occurring, but it is not expressed in terms of attenuation but rather by an acceleration of the response *and* its dissipation.

Accidents

Despite a monotonic decline in the fatal accident rate from year to year, few effects are actually significant except for the coefficient on 2004 (relative to 2001), which is individually significant, though not after the Bonferroni adjustment. The year coefficients are also not jointly significant ($p = .09$). The monthly pattern shows that fatal accident rates tend to be higher in the summer and are about 64 percent greater during holidays. Relative to Saturdays, all other days have significantly lower rates except for Fridays.

Looking at both periods in Table 4, the day 3 increase in fatal accidents (Stecklov and Goldstein 2004) identified solely during Period 1 continues to be significant ($p = .01$). However, change over time is more difficult to detect. The average effect over the two time periods studied is a 25 percent increase in the traffic fatality rate on the third day after an attack (Table 4). This average is a combination of a 35 percent ($p = .01$) increase in period one and an insignificant 11 percent increase in period two. While this might be indicative of habituation – it is too imprecise to reject the hypothesis of no decline in the day-three effect.

An argument could be made that this pattern offers evidence of habituation given the large decline in the coefficient value between periods 1 and 2, and that the Period 2 estimate is not significantly different from zero. On the other hand, tests for a change of this day-3 effect over time are inconclusive. The interaction test for a change is not significant (p = .25), making it difficult to claim attenuation. Also, the Period 2 coefficient on the day-3 lag, which is still positive and substantively significant–though not statistically–equals 1.11, indicating an 11 percent increase in the fatal accident rate.

Focusing exclusively on large attacks lends greater credence to claims of persistence rather than habituation. The Period 1 day-3 effect of a 67 percent increase in

Table 3: Estimated Effects of Terrorism from Past Months and Recent Days on Traffic Volume

	Traffic Volume				Fatal Accident Rates			
	All Fatal Attacks		Large Fatal Attacks		All Fatal Attacks		Large Fatal Attacks	
Cefficient	Short Memory	Long Memory	Short Memory	Long Memory	Short Memory	Long Memory	Short Memory	Long Memory
Terror 0 Lag	.978	.978	1.004	1.001	1.100	1.101	1.103	1.075
	(.129)	(.131)	(.900)	(.969)	(.317)	(.316)	(.613)	(.710)
Terror 1 Lag	.978	.979	.969	.967	1.024	1.029	1.047	1.026
	(.130)	(.142)	(.311)	(.280)	(.812)	(.772)	(.820)	(.897)
Terror 2 Lag	**.951**	**.951**	**.928**	**.925**	1.049	1.047	.933	.900
	(.001)	**(.001)**	**(.021)**	**(.016)**	(.630)	(.641)	(.756)	(.635)
Terror 3 Lag	.973	.974	.961	.961	**1.253**	**1.267**	1.271	1.257
	(.065)	(.076)	(.190)	(.181)	**(.013)**	**(.009)**	(.178)	(.199)
Terror 4 Lag	1.001	1.001	1.009	1.008	1.032	1.039	1.205	1.189
	(.956)	(.921)	(.770)	(.789)	(.744)	(.694)	(.294)	(.331)
Terror 5 Lag	1.015	1.015	1.012	1.01	1.043	1.043	.989	.962
	(.304)	(.306)	(.701)	(.749)	(.665)	(.661)	(.956)	(.845)
Terror Days 6-30	**1.01**	**1.01**	**1.01**	**1.008**	1.00	.99	1.00	.997
	(.002)	**(.008)**	**(.005)**	**(.016)**	(.915)	(.741)	(.913)	(.883)
Terror Days 30-60		1.00		1.001		1.03		1.033
		(.637)		(.617)		(.089)		(.090)
Terror Days 60-90		**1.01**		**1.007**		**1.06**		**1.059**
		(.025)		**(.012)**		**(.001)**		**(.002)**
Terror Days 90-180		1.00		1		1.01		1.006
		(.770)		(.922)		(.481)		(.573)
Observations	1,301	1,301	1,301	1,301	1,301	1,301	1,301	1,301
R-squared	.53	.532	.525	.528				
Chi-2					69.901	83.584	65.277	78.053

Notes: Significant coefficients (exponentiated) and p-values estimates (in parentheses) are in bold. Linear regression using logged values of traffic volume and fatal accident rates estimated with Poisson regression. All models include controls seen in Table 1 including year, month of year, day of week and holiday.

Table 4: Poisson Regression Estimates of Terror Effects on Daily Traffic Fatality Rates

	Traffic Fatality Rate							
	All Fatal Attacks				Large Attacks (> 9 fatalities)			
Coefficient	Periods 1 & 2	Period 1	Period 2	Periods 1 & 2	Periods 1 & 2	Period 1	Period 2	Periods 1 & 2
Terror 0 Lag	1.1	1.031	1.164	1.024	1.104	1.135	1.074	1.193
	(.319)	(.809)	(.306)	(.851)	(.611)	(.641)	(.799)	(.511)
Terror 1 Lag	1.023	.945	1.163	.947	1.047	.757	1.292	.783
	(.818)	(.668)	(.315)	(.675)	(.817)	(.374)	(.332)	(.430)
Terror 2 Lag	1.048	1.064	.993	1.077	.933	1.071	.661	1.123
	(.633)	(.623)	(.967)	(.554)	(.756)	(.808)	(.278)	(.674)
Terror 3 Lag	**1.252**	**1.354**	1.108	**1.359**	1.271	**1.671**	.799	**1.765**
	(.013)	**(.010)**	(.496)	**(.008)**	(.178)	**(.021)**	(.484)	**(.009)**
Terror 4 Lag	1.032	.946	1.188	.939	1.206	.601	**1.841**	.625
	(.748)	(.681)	(.229)	(.631)	(.293)	(.118)	**(.005)**	(.145)
Terror 5 Lag	1.042	1.112	.911	1.095	.989	.99	1.033	1.063
	(.668)	(.396)	(.557)	(.453)	(.957)	(.972)	(.909)	(.818)
Period x Terror 0 Lag				1.131				.889
				(.524)				(.761)
Period x Terror 1 Lag				1.198				1.626
				(.361)				(.231)
Period x Terror 2 Lag				.904				.58
				(.628)				(.247)
Period x Terror 3 Lag				.806				**.442**
				(.254)				**(.035)**
Period x Terror 4 Lag				1.242				**2.902**
				(.268)				**(.006)**
Period x Terror 5 Lag				.847				.916
				(.412)				(.827)
Observations	1,301	521	780	1,301	1,301	521	780	1,301
Chi-squared	69.89	5.658	41.204	75.519	65.265	51.046	46.972	82.699

Notes: Significant coefficients and p-values estimates (in parentheses) are in bold.
All models include controls seen in Table 1 including year, month of year, day of week and holidays.

the fatal traffic accident rate is replaced by a Period 2 day-4 effect of an 84 percent increase. The former loses significance after the Bonferroni adjustment. While the temporal shift might be interpreted as real, a more skeptical interpretation might focus on random variation as the apparent cause. It is probably more reasonable to interpret this as a continuation of a powerful lagged effect rather than any real shift in the underlying behavioral response. Ten large attacks in each of the periods probably does not provide sufficient power to capture such shifts with accuracy. The day-3 or day-4 effects in each of the two periods are most likely identifying the same process, which appears to have lost little power over time. Finally, another sign of persistence is the manner in which the coefficient for small attacks on the third-day lag remains nearly unchanged from 1.255 to 1.247 (not shown).

An additional set of models provides further support for claiming consistency over time. First, in Table 3 we repeat the earlier memory test where measures for the total number of fatal terrorist attacks in previous months are introduced into the regression. As with the volume results, the effects of terror in the immediate past is unchanged when the potential mediating variables are introduced. This is apparent when looking at all attacks as well as large attacks, although the latter result is less relevant given that the main effect of large attacks is not significant for the entire period. Furthermore, an interaction between the total number of terrorist attacks from 60-90 days prior with terrorist attacks three days earlier – the test of a moderator effect of past terror – is not significant.

Discussion

There is intense interest in understanding how populations react to traumatic events, including natural disasters as well as man-made disasters and violence. Terrorism has emerged in the 21st century as a central form of inter-societal violence with consequences across a wide range of personal and social activities. In this article, we examine a fundamental question that cannot be examined in the context of most other forms of societal trauma: does repeated exposure to endemic terrorism in Israel lead to a process of habituation whereby the effects of terror attenuate or do populations become increasingly sensitized to terror through repeated exposure.

Our results provide overall support for earlier published findings on the effects of terrorism on traffic volume and accident rates. Over the entire four-year period, traffic is reduced on the day of the attack and three subsequent days, but only the 5 percent decline on the second day following fatal terrorist attacks is significant. Similarly, we find a 24 percent increase in fatal traffic accident rates on the third day following terrorist attacks. The results tell us that there is a reaction that can be measured using traffic data, that this reaction is not immediate but delayed, and that the impact of terrorism on both the amount people drive and the "quality" of their driving also dissipates by the fourth or fifth day following an attack. Our analysis also provides new evidence on how the impact of terror on current behavior may reverberate over the course of time.

In particular, we find that the effects of terrorist attacks in previous months continue to influence behavior but only for some three months.

Our main findings indicate that there is little or no habituation or sensitization to terror attacks in the traffic data. These results are most consistent with persistency in the response to terror attacks over the course of the 2nd Intifada. This is evidenced by the lack of change in the response over time. It is further clarified when we test whether current terror effects are moderated by the level of terror in prior months. These effects indicate continuity of impact, regardless of the level of violence experienced. Stability in the reaction to terror is interesting in light of limited evidence suggesting that recurrent disasters produce increased social resiliency, particularly where social institutions and social capital provide a sufficiently stable context (Adger 2005; Samanta 1997). In Israel, while social institutions are strong (Kimmerling 1985), the political nature of attacks and their focused impact may not create the same degree of shared experience and social resiliency, reducing the potential for social habituation.

Both approaches used to test for habituation rely on a specific null hypothesis test. A lack of significance in the test of the interaction coefficient is either because the null hypothesis is true or because we lack the statistical power to reject the null. Earlier analysis found no interaction between time and terror attacks but these findings were treated cautiously because of the relatively short duration studied and low number of terror attacks (Stecklov and Goldstein 2004). In contrast, the current analysis includes more observations and the statistical power is increased. With a standard error of .03 on the interaction coefficient, effects larger than 6 percent should be detectable. Thus, while we cannot conclude that there is no effect we can be reasonably confident that the change in the effect over time is less than 6 percent.

And despite the overall impression of stability in our findings, there are also signs in the data–albeit statistically weaker ones–that the population-level reaction to terror has been accelerated, appearing more quickly but also dissipating more rapidly. This unexpected shift is difficult to interpret specifically in terms of either sensitization or habituation. Instead, a shift in the timing of the effect may itself represent a form of social habituation that develops over time as the response is accelerated. To the extent that habituation is a form of adaptive learning, both individuals and society might habituate to terror by developing new norms of response. The introduction of these customs over time produces a learned reaction. The evolution of a norm, in this sense, may be precisely the sort of effect that we observe in the traffic volume results. While reasonable, far more research is needed to explore how behavioral patterns emerge during periods of intense violence, such as terror attacks, and to substantiate our findings with alternative behavioral measures.

Notes

1. Fatal traffic accident rates are also used in Stecklov and Goldstein (2004).
2. The largest gap is from Dec. 7, 2003 to March 9, 2004 during which all data was irretrievably lost due to computer problems at the Ayalon Management Freeway Company. There is no statistical difference in the mean level of terror attacks between periods with and without traffic volume data.
3. Simple tests of bivariate correlations between the lags indicate that the average correlation is under 4 percent and none of the values exceed 9 percent while the VIF is near "1."
4. The last date included in the analysis of the first paper is almost identical to the date at which half of the total, cumulative fatalities from terrorism over the four- year period occurred.

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