Terror attacks influence driving behavior in Israel

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Edited by Stephen E. Fienberg, Carnegie Mellon University, Pittsburgh, PA, and approved August 17, 2004 (received for review April 7, 2004)

Terror attacks in Israel produce a temporary lull in light accidents followed by a 35% spike in fatal accidents on Israeli roads 3 days after the attack. Our results are based on time-series analysis of Israeli traffic flows, accidents, and terror attacks from January 2001 through June 2002. Whereas prior studies have focused on subjective reports of posttraumatic stress, our study shows a population-level behavioral response to violent terror attacks.

Terror attacks are thought to have profound, society-wide consequences that extend far beyond the immediate victims of the violence, but until now there has been little empirical evidence of population-wide effects (1). Here, we use traffic flow and automobile accident statistics in Israel to explore the societal consequences of terror attacks. Analyzing an 18-month period that included a large number of terrorist attacks, we find a lull in the light accident rate the day after an attack followed by a spike in traffic accident fatalities 3 days after an attack. The effects on accidents are proportional to the severity of the attack. The results suggest that terror attacks in Israel have broad, short-term behavioral effects on the general populace.

Past research on the societal consequences of terror, using after-the-fact surveys, has found a rise in posttraumatic stress disorders after the 9/11 terror attacks (2–5). However, survey data, collected anywhere between 3–5 days (2) and 1–2 months (4) after the attack, is ill-suited for measuring change and does not allow attribution of such change to the attacks themselves. An additional problem with postterror surveys is that they consistently suffer from substantial nonresponse rates generating unknown bias (2–5).

There is, in fact, little observational evidence of broad, societal responses to terror. Public reports of New York City murder declines reported in local newspapers after the 9/11 attacks are an interesting example of a possible societal response (6). However, in the context of several years of declining crime levels and huge increases in security operations in the area after the 9/11 terror attacks, these changes are difficult to attribute to the attacks themselves.

The recent National Academy of Sciences panel report (1) on the social dimensions of terror is generally critical of the quality of available evidence about the social consequences of terror. Notably, their analysis rests primarily on empirical evidence based on studies on the social response to disasters (7) or on investigations of civilian responses to massive bombings during World War II (8). They note that much of the related literature "relies on hastily assembled journalistic reports and after-the-fact accounts based on recollections by participants" and that such sources are "subject to selectivity and distortion."

Our method measures the immediate behavioral consequences of specific terror attacks. The use of daily time-series of traffic accidents and the larger number of terror attacks in Israel provides a better basis for making causal inferences, although statistical evidence alone can never be entirely definitive. Because our findings are based on repeated tests of daily fluctuations in the time series, it is unlikely that the spurious events would always occur in synchrony with each terror attack. It is also possible that chance fluctuations are responsible, the probability of which we are able to assess by using statistical methods. The models we use enable us to eliminate some alternative explanations. For example, our data suggest that terror attacks and driving accidents are both more likely to occur on Sundays, the beginning of the actual work week in Israel (>25% of all terror attacks in our data file occurred on Sundays, as opposed to <10% on Mondays, Fridays, and Saturdays). The introduction of day-of-week controls enables us to overcome these and other potentially spurious explanations and to obtain a more reliable estimate of the short-term behavioral consequences of terror.

The use of traffic accident injury and fatality data to gauge the behavioral response to terror attacks is motivated by the positive association between psychosocial stress and traffic accidents (9–11). Driving behavior is linked to aggression, stress, and frustration (10, 12, 13). Interestingly, studies have shown that suicides, traffic fatalities, and airplane accidents often increase after well publicized suicides and murders (14–17). The literature has argued that some portion of traffic fatalities are, in fact, disguised suicides (16, 18, 19).

Although terror-induced stress can be expected to increase motor vehicle accident rates, other possible explanations lead to less clear predictions. If terror attacks lead societal members to increased feelings of shared vulnerability or social solidarity (1), they might very well respond by reducing their aggressiveness on the road. A similar explanation has been suggested for the decline in health worries in Israel during times of national stress (20). A different type of social psychological explanation, relying on individualized responses to perceived threats, suggests that some individuals respond with more cautious behavior and others respond with more risk-taking (21–23). Alternately, individualized responses to terror might shift the composition of drivers after a terror incident, increasing or decreasing accident rates.

The consequences of terror attacks in Israel may differ from those in other countries. The terror attacks in Israel stand out because of their high frequency. Furthermore, Israel is a small and tightly knit society where the population is constantly in touch with news reports of terror events and tragedies and where society is well organized to deal with war (24). Still, our findings offer insight into the population-level consequences of repeated terror attacks. Terror attacks have short-term effects on the general population, but the pattern of evidence also hints at a relatively rapid return to normalcy.

Data and Methods

We use a daily record of terror incidents obtained from the database of the Interdisciplinary Center of Herziliya (www.ict.org.il), checked against a list kept by the Israel Ministry of Foreign Affairs (www.mfa.gov.il/mfa). We included all terror attacks with at least one fatal casualty that took place within Israel, excluding the West Bank and Gaza. We classified terror incidents into two overlapping levels of severity: all attacks with 1 or more deaths; and large attacks with 10 or more deaths. The timing and number killed in each of the 63 terror attacks

This paper was submitted directly (Track II) to the PNAS office.

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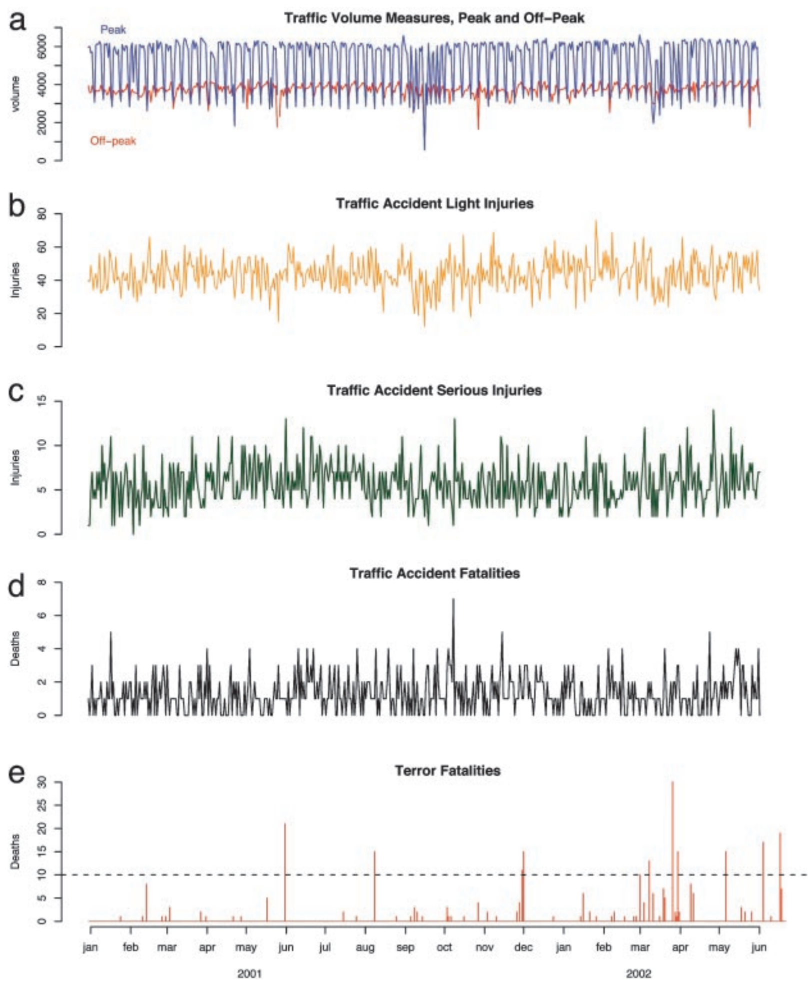

Fig. 1. Time series for traffic volume, traffic accidents, and terror fatalities in Israel from January 1, 2001, to June 22, 2002. (*a*) As measured on the Ayalon Freeway by the Ayalon Freeway Management Company. Traffic volume is a measure of the average flow of vehicles per hour. Peak traffic hours refer to traffic between 5 a.m. to 10 a.m. and 3 p.m. to 8 p.m. Off-peak traffic hours refer to 10 a.m. to 3 p.m. and from 8 p.m. to 5 a.m. (*b–d*) All three accident categories refer to the number of persons injured or killed in automobile-related accidents. Light accident injuries refer to injuries that require no more than 24 h of hospitalization. Serious accident injuries refer to those requiring >24 h of hospitalization. (*e*) Terror fatalities defined as terror events within Israel (excluding West Bank and Gaza) with at least one Israeli fatality. The dashed line marks particularly large terror attacks with 10 or more fatalities.

included in our data are shown in Fig. 1*e*, where the horizontal dashed line distinguishes the large attacks.

Our main analysis is limited to the period from January 1, 2001, to June 22, 2002, because this is the period for which traffic volume data are available (see Fig. 1*a*). We use the most recently available data on the number of daily traffic accident injuries and fatalities published by the Israel Central Bureau of Statistics (see Fig. 1 *b–d*). We follow the police categorization of accident injury and fatality statistics into three categories: light injuries, serious injuries, and fatalities. Light injuries refer to injuries sustained in a traffic accident requiring either no medical attention or hospitalization of no more than 24 h. Serious injuries required hospitalization for >24 h. Because our data are based on injuries and fatalities, accidents with no injuries are excluded from the analysis.

We measure traffic volume by using data collected from sensors placed at four separate points along Israel's primary commuter freeway, the Ayalon near Tel Aviv. (Statistics were obtained from the roadway databases of the Ayalon Freeway Management Company). We look at the sensor data in two ways. First, we construct a measure of traffic volume over each 24-h period. This measure is used to convert the daily counts of accident injuries and fatalities into estimates of daily accident injury and fatality rates.¶ Second, we differentiate between rush hour and more discretionary, off-peak traffic volume to distinguish the effects of terror on work-related versus discretionary traffic patterns. We define rush hour as 5 a.m. to 10 a.m. and 3 p.m. to 8 p.m., with all other times being "off-peak."

Looking at Fig. 1, we see that terror attacks occur with high frequency, averaging nearly one per week, and become more common in the spring of 2002. Traffic accidents show no long-term trend over the time period. Day-to-day fluctuations are large, following a weekly pattern but also demonstrating a large random component.

No link between attacks and accidents is visible looking at the raw time series. The day-to-day variability masks any effect of each bombing. In Fig. 2, we redisplay the time series of

¶These "rates" are better thought of as "pseudo-rates," because the accident counts are for the entire country and the volume counts are for the Ayalon freeway only. However, we believe the Ayalon volume statistics are a good proxy for national volume because the Ayalon is Israel's most traveled freeway and is used for commuting, longer-distance north–south travel, and shorter-distance suburban travel. The daily traffic volume statistics show an average of ≈100,000 cars per day over our period of study, with a range of between 23,300 and 121,400 cars.

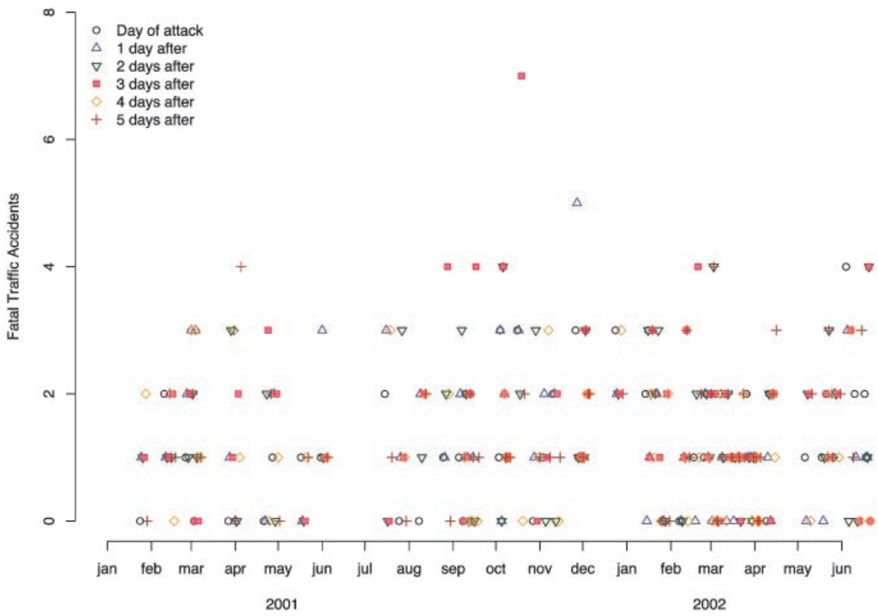

Fig. 2. Israeli traffic fatalities by days after terror attack. Fatalities are shown only for days within a 5-day period after fatal terror attacks.

traffic fatalities, showing their relation to the timing of terror attacks. The preponderance of day-three lags among the high fatality days in Fig. 2 suggests that there may be an increase in traffic fatalities 3 days after a terror attack. Even ignoring the unusually large number of accident fatalities on October 21, 2001 (seven fatalities), there are still unusually many high-fatality days occurring 3 days after attacks. However, from Fig. 2, it is impossible to determine how large such an effect might be and whether it may be due to chance or spurious in nature.

We use statistical methods to both control for other determinants and to identify the effects of terror on traffic for the whole period. Distributed lag regression models (17, 25), with dummy variables for each of the five days after attacks, were used. The models include day-of-week and seasonality factors including month and year, as well as major holidays, allowing us to control for various spurious effects. These spurious effects could result, for example, from the tendency for terror attacks to take place on specific days of the week. The coefficients of the models tell the proportional change in traffic volume or accident rates in the days after a terror attack.

The statistical model for traffic volume is

$$V(t) = b_0 L_0^{X_0(t)} L_1^{X_1(t)} L_2^{X_2(t)} L_3^{X_3(t)} L_4^{X_4(t)} L_5^{X_5(t)} \prod_{i} b_i^{Z_i(t)},$$

where $V(t)$ is the traffic volume on day t at either peak or off-peak hours, L_i is the lag i effect of a bombing at time $t - i$, $X_i(t) = 1$ if there was a bombing on day $t - i$ and 0 otherwise, and b_i is the effect of covariate Z_i. The covariates include day of week, month of year, year, and major holidays, including Passover, Yom Kippur, Purim, Holocaust Remembrance Day, Jewish New Year, and Israeli Independence Day (we use a common dummy for all holidays, though we have found that using separate dummies for each holiday does not change the result). The traffic flow model is fit by taking logarithms and using ordinary least squares. Separate models are fit for peak and off-peak traffic volume data.

The model for accident rates takes a similar form

$$\frac{A(t)}{V(t)} = b_0 \lambda_0^{X_0(t)} \lambda_1^{X_1(t)} \lambda_2^{X_2(t)} \lambda_3^{X_3(t)} \lambda_4^{X_4(t)} \lambda_5^{X_5(t)} \prod_{i} b_i^{Z_i(t)},$$

where $A(t)$ is the number of accident victims on day t and separate models were estimated for light, serious, and fatal accidents. In this model, λ_i is the lag i effect of a terror attack at time $t - i$. This model is estimated by using Poisson regression with volume $V(t)$, the volume of traffic on day t, as an offset, an approach that gives appropriate standard errors for rates (26).

Our use of multiplicative models assures that the effects we measure are proportional to the prevailing traffic flow or accident rates. In fact, our results turned out to be rather insensitive to correcting for actual traffic volume. We have also estimated additive models and autoregressive models that account for the serial correlation in errors as well as testing for the sensitivity of our results to the inclusion of more lag terms. The substantive results we report here are robust across these different model specifications. We used a simple dummy variable formulation to capture the effect of terror on the day of the attack and on each of the 5 preceding days. An alternative approach is to include a measure of the actual number of terror casualties on each of these days. Our testing suggested that the two approaches led to substantively similar conclusions. We prefer the dummy variable approach, which does not require us to assume a specific functional relationship between the magnitude of terror attacks and their effect on traffic.

The exploratory nature of our statistical analysis, in which multiple lags were examined for possible effects, means that caution should be taken in interpreting traditional measures of statistical significance. A more conservative approach is to adjust for multiple comparisons by using the Bonferroni method to multiply the P values on lagged effects we report in the text by 6, the number of lags considered (27). For example, the P value of 0.007 we report for the 3-day lagged 35% increase in fatal accidents after terror attacks can be more conservatively interpreted as $6 \times 0.007 = 0.042$. The chance that this finding is due to random fluctuations in traffic accident rates is thus probably closer to 1 in 20 rather than the <1 in 100 that the reported P value would indicate. All P values given in the text refer to the unadjusted single comparisons and may be adjusted by using this approach. In Fig. 3, we use both approaches, showing that the

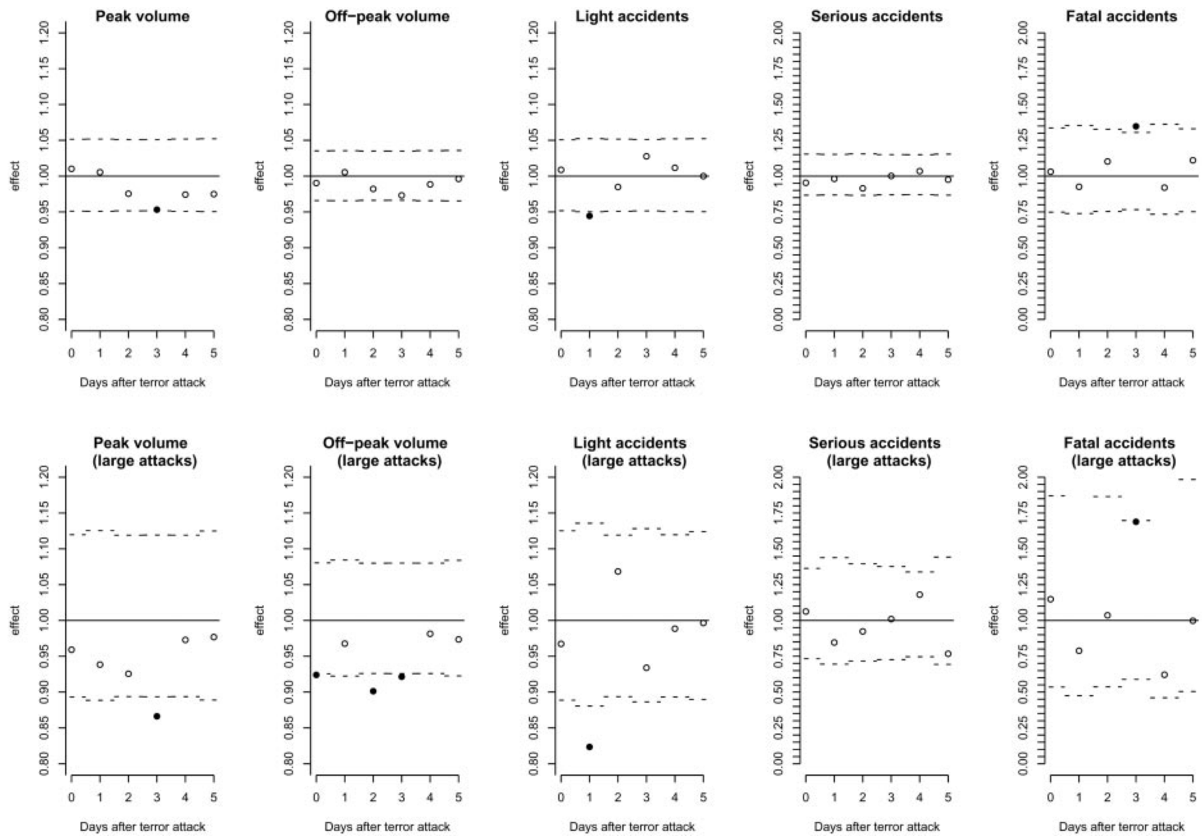

Fig. 3. Model estimates of proportional effects of terror attacks on traffic volume and accident rates by number of days after attack. (*Upper*) Results for all attacks. (*Lower*) Large attacks only. Open circles indicate statistically insignificant effects; filled circles indicate effects that are individually significant at the 5% level; circles that lie outside of the dashed interval are statistically significant at the 10% level using the Bonferroni adjustment for multiple comparisons. See text for details.

overall effect of terror incidents appears robust to the multiple comparisons adjustment.‖

Results

Our main results are presented in Fig. 3: each panel shows the proportional effect of terror attacks on traffic volume or traffic accident injury or fatality rates for the indicated lag (full model results are included in Tables 1–4, which are published as supporting information on the PNAS web site). The filled points indicate coefficients that are statistically different from zero at the 5% level, considering each coefficient on its own. These are the P values that we discuss in the text. The dashed lines cover a 90% interval around the null that there is no effect at any lag and adjust for the multiple comparisons being made over all of the lags. As can be seen, nearly all of the individually significant points also lie outside the null interval.

Traffic Volume. We look separately at the effect of terror on traffic volume measured during the peak, rush-hour traffic hours and off-peak traffic hours. We had hypothesized that discretionary travel would be influenced more strongly by terror attacks, whereas work-related travel would continue mostly unabated. Contrary to our expectations, we found declines in traffic volume in both peak and off-peak hours, with a decline during peak hours of 4.7% ($P = 0.02$) on day 3. The decline in volume for traffic in off-peak hours was somewhat less, reaching 2.7% ($P = 0.06$) on day 3, but following a similar temporal pattern.

The results suggest that traffic volume remains stable on the day of and the day immediately after a terror incident, declines several days after the attack, and that the effects of terror on traffic dissipate within 4–5 days. When we restrict the analysis to larger terror attacks, we find that traffic volume during peak hours again declines on the third day after the terror incident, but by 14.7% ($P = 0.00$) (Fig. 3 *Lower*). Whereas the effects of all fatal attacks on traffic volume was similar for peak and off-peak traffic volume, the effects of large terror attacks is different for the two types of traffic volume. Large terror incidents apparently lead to immediate changes in people's interest and willingness to venture out. We find that, after large terror attacks, off-peak traffic volume immediately declines by 7.8% ($P = 0.02$) on the day of the incident, 10.4% ($P = 0.00$) 2 days after the incident, and 8.1% ($P = 0.01$) 3 days after the incident. As we found earlier, the effect appears to dissipate within 4–5 days with large terror attacks as well.

Traffic Accident Rates. We analyze all three types of reported accident injuries, including light, serious, and fatal injuries. Terror attacks have no detectable effect on the light accident injury rate on the day of an attack, but reduce it by nearly 6% ($P = 0.01$) the day after an attack. This effect is brief, lasting only 1 day, and by day 2 after the attack there is no remaining impact. Larger attacks have a greater impact, although the timing is

‖To create a 90% confidence region with a significance level of $\alpha = 0.10$, we use the Bonferroni corrected significance level of $\alpha^* = \alpha/6 = 0.0167$. 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 shown in Fig. 3 use $\pm$ 2.39 standard errors, covering the desired $1 - \alpha^* = 0.9833$ interval.

unchanged: large attacks reduce light accident rates by 18% ($P = 0.00$) the day after the attack.

Taken at face value, the decline in the light accident rate could be caused by safer driving. In discussions, police officials have suggested that increased police presence after terror incidents may encourage drivers to behave more cautiously. However, the apparent decline may also be due to a reduction in light-injury accident reporting. Drivers involved in minor accidents, who would otherwise be concerned about filing reports to guarantee potential insurance claims, might, subsequent to the attacks, feel that such actions would be egotistical or mundane at a time of shared tragedy and social solidarity. The fact that we find a day-after-attack decline only in light accidents, but not in serious or fatal accidents, points toward a change in reporting behavior rather than safer driving.

We found no statistically significant effect of terror on the serious accident injury rate. However, serious accident data classification is thought to vary considerably by jurisdiction and over time, according to police officials. This lack of consistent reporting may make it difficult to detect changes in accident rates.

Reporting is most reliable for fatal accidents. Here we find no day-0, day-1, or day-2 effects of terror, but an increase of almost 35% ($P = 0.01$) in the rate of traffic fatalities 3 days after terror attacks. This effect persists even when the October 20 outlier is excluded from the analysis.[††] Furthermore, we find that third-day effect of large terror attacks is even larger, with a 69% ($P = 0.02$) increase in traffic fatalities. The estimated parameters indicate a considerable effect of terror on the number of traffic fatalities in Israel. There are an average of 1.3 traffic fatalities per day in Israel during this period, or a total of 689 traffic fatalities over the entire interval. When the estimated 35% percent effect of all terror attacks on day 3 fatal traffic accident rates is used, our results suggest that terror causes $\approx$0.4 additional traffic fatalities after each terror incident, or a total of 28 extra traffic deaths over the entire period.

Why traffic fatalities increase on the third day after a terror attack remains a puzzle. The decline in traffic volume on day three could paradoxically increase fatalities, because less traffic allows higher speeds, but research on the effect of congestion on traffic fatalities generally indicates a positive, although often complex and nonlinear, association between traffic volume and accidents (28, 29). All other things equal, we would have expected a decline in traffic volume to have produced a decline, not an increase, in fatalities.

Interestingly, the 3-day lag we find is similar to that found in studies on imitative suicides (16, 17), in which well publicized suicides are followed 3 days after with a rise in traffic fatalities. A similar 3-day spike in homicides is also found after major boxing matches (30). Some fraction of the increase in traffic fatalities after terror attacks may be attributable to covert suicides and/or increased aggression on the road. One piece of evidence supporting the idea that covert suicides may be playing a role is the lack of any apparent increase in serious accidents at the same time that fatal accidents increase. However, it is difficult to directly test the covert suicide hypothesis in Israel by using data on suicides. Suicide data in Israel are considered unreliable because of religious restrictions on the burial of suicide victims in Jewish cemeteries.

Other nonsuicide explanations should also be considered. For example, the day-three increase in fatalities coincides with the time when those exposed to terror may try to return to their normal routines but are not yet psychologically, and perhaps physiologically, sufficiently recovered. Yet another explanation for the 3-day lag is that it is a counterreaction to the collective bonding that occurs immediately after the terror event, similar to the "post-suppression rebound" found in experimental psychology (31, 32).

We have emphasized the presence of detectable effects of terror in the immediate aftermath of attacks. In addition, there is a notable lack of longer-term effects beyond the 3-day spike in fatal accidents. Days four and beyond have normal levels of traffic volume and accidents and suggest that the effects of terror are transient. We looked for changes in the magnitude of the short-term effects by introducing interaction terms with time and with the cumulative number of bombings, but found no clear indication that the Israeli population was becoming either more sensitive or more resistant to terror attacks over time, at least over the period covered by our data.

Discussion

The use of aggregate behavioral outcomes as a measure of psychosocial well-being pioneered in the 19th century by Durkheim continues to be fruitful, particularly given the expansion of routine data collection systems. A modern next step could be the analysis of biomarker data to assess population stress levels in the aftermath of terror. This would allow a narrowing down of the causal pathways that connect terror attacks with postterror outcomes.

The third-day spike in traffic fatalities suggests that terror attacks have indirect effects as well as immediate casualties. Some portion of this increase in traffic fatalities may be terror-induced suicides. However, the increase may also reveal a more general delayed reaction to violence and stress. Further research might evaluate whether the response to terror attacks is much different from the response to other forms of social trauma. There is also a need to look at other indicators of population level reactions to terror attacks, for example, changes in the incidence of domestic violence or increased cigarette consumption, both to corroborate (or to contradict) the results presented here and to help comprehend the breadth of terror's impact on society.

If increased stress is indeed responsible for the increase in traffic fatalities, this stress may also have long-term consequences for stress-related illnesses such as heart attacks. These effects, even if large, may be difficult to detect because their effect may be spread over months and years. In the short term, however, our results suggest that attention be paid to the psychological well-being of the population in the several days after terror attacks.

[††]Without the October 20 outlier, we found a day-3 increase of 27% in traffic fatalities ($P = 0.04$) in the model for all terror incidents, and a day-three increase in 68% ($P = 0.02$) in the model for large terror incidents.

We thank Michael Beenstock, Kenneth A. Bollen, Marcia Castro, Roni Factor, Bonnie Ghosh-Dastidar, Eugene Hammel, Arie Kruglanski, Tova Rosenbloom, Eldar Shafir, Burton Singer, and Kenneth Wachter for helpful suggestions.

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