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AFFECT GENERALIZATION AND THE PERCEPTION OF RISK(U)  
STANFORD UNIV CA DEPT OF PSYCHOLOGY E J JOHNSON ET AL.  
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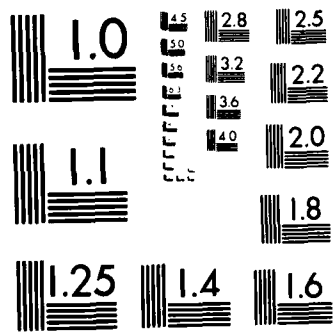
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Affect, Generalization, and the Perception of Risk<sup>1</sup>

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20 July 1982

**Abstract**

Experimental manipulations of affect induced by a brief newspaper reports of a tragic event produced a pervasive increase in subjects' estimates of the frequency of many risks and other undesirable events. Contrary to expectation, the effect was independent of the similarity between the report and the estimated risk. An account of a fatal stabbing did not increase the frequency estimate of a closely related risk, homicide, more than the estimates of unrelated risks such as natural hazards. An account of a happy event which created positive affect produced a comparable global decrease in judged frequency of risks.

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As a society, we have never been more concerned with the assessment, the management and the regulation of risk. Because public reaction to hazards from pesticides, nuclear power, or food additives appear to influence the regulation and management of these technologies, it is important to understand how the lay person perceives and evaluates risks. This is particularly true for hazards such as terrorism, nuclear power or genetic engineering, where the available statistical data are very limited, and the assessments of the risks are based on subjective and intuitive judgments.

Indeed, psychologists and other researchers have shown increasing interest in the manner in which people perceive and estimate the severity of various risks. Lichtenstein, Slovic, Fischhoff, Layman, and Combs (1978) asked lay people to estimate the number of deaths per year that are due to various hazards. These investigators found that the subjective estimates were quite consistent across several methods of elicitation, and correlated reasonably well (median  $r$  of .7) with actuarial estimates of frequency. A comparison of objective and subjective estimates revealed two biases. The primary bias, refers to the common tendency to overestimate infrequent causes of death while underestimating more frequent causes. Thus, a relatively rare cause of fatality, polio, was estimated to be about ten times more frequent than in actuality, while a common cause, lung cancer, was underestimated by about a factor of ten. The secondary bias, refers to the observation that "overestimated causes of death were generally dramatic and sensational whereas underestimated causes tended to be unspectacular events, which claim one victim at a time..." (Slovic, Fischhoff and Lichtenstein, 1982, p.467). This bias can be attributed to the availability heuristic in which one estimates the frequency of a class by the ease with which its instances are brought to mind (Tversky and Kahneman, 1973). For example, homicide is perceived as more frequent than suicide, and twice as many people are thought to die from fire than from drowning. Actually, this is not true. About 6000 more people die in suicides than in homicides, and drowning causes death about as frequently as fire. Lichtenstein et al. suggest that these errors could reflect an availability bias induced by the media, which report homicide and fire more frequently than suicide and drowning. A content analysis of newspaper reports (Combs and Slovic, 1979) supported this interpretation.

### Cognition and Affect in Risk Perception

One characteristic that distinguishes judgments about risks from other estimates, such as letter frequency, is that they seldom occur in an emotionally neutral context. When we witness an accident, or read a newspaper report about a natural disaster, we do not merely revise our subjective probabilities; we are also shaken and disturbed. Our encounters with news about risk and death commonly generate fear, anxiety and worry. Imagine that you had just read a disturbing newspaper account of, say, the senseless shooting of an innocent passerby. Such an account, and the emotional response it elicits, may well increase your estimate of the number of deaths due to homicide, more than justified by the information contained in the report.

To investigate the role of affect in judgments of risk we constructed brief accounts of tragic deaths of a single person from a specific cause. Like many newspaper stories, our accounts described details of the tragic incident, but gave no information about its prevalence. Thus the stories were designed to generate affect while conveying minimal data about the frequency of the relevant hazard in the general population. The effect of these stories on the perceived frequency of deaths caused by various risks was studied by comparing estimates made by two groups: one who had read the stories and another who had not.

We consider four possible effects of the experimental treatment, ordered by the range of their impact. (1) The stories may have no effect on estimates of fatalities. This appears to be a normatively appropriate response since the stories, which describe the death of a single person, do not justify significant changes in frequency estimates.

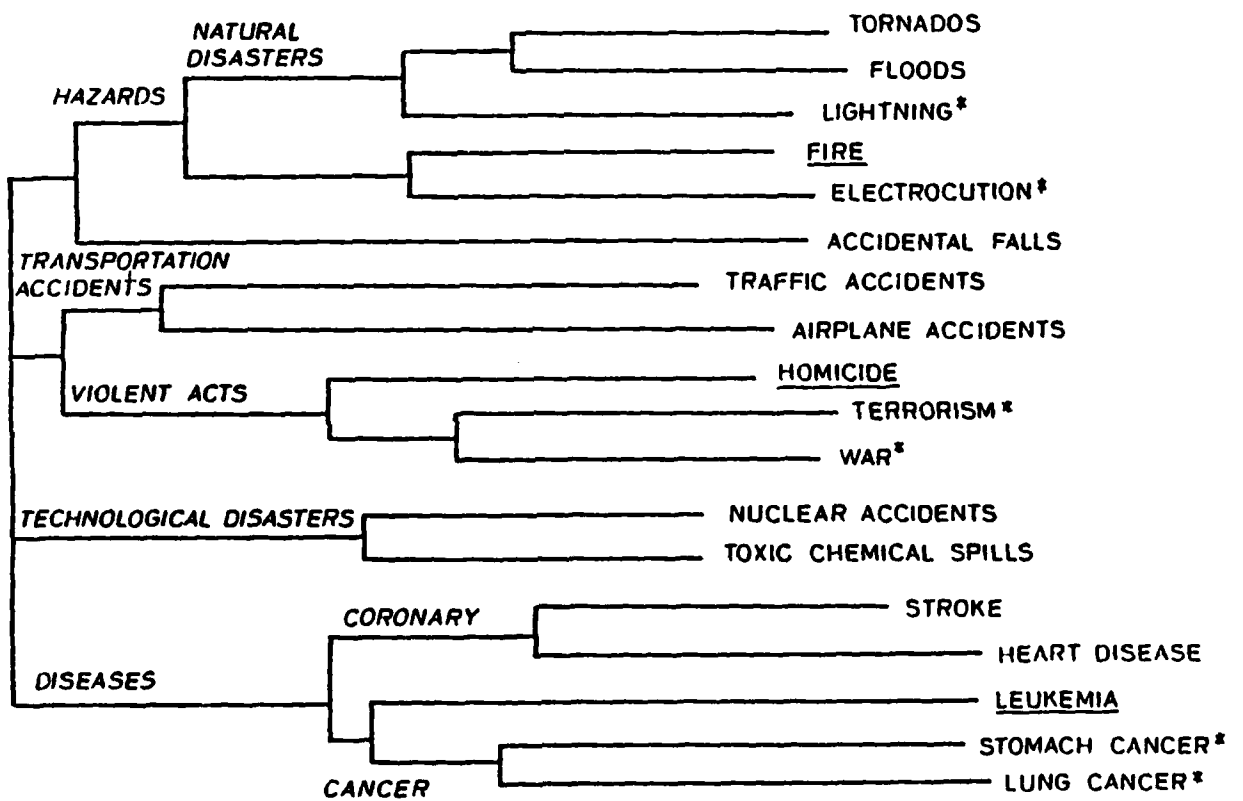
(2) The stories may produce a local effect. That is, a story about homicide may increase the estimated frequency of homicide, etc. This could be caused by several mechanisms. The incident described in the story could serve as a retrieval cue, making similar instances more available, thereby increasing the judged frequency of the relevant risk. The subject in the study, like the reader of a newspaper, could also make the inference that the selection of a story about a particular cause of death indicates that this risk is especially serious or prevalent. Either mechanism results in a local increase, that is, a higher frequency estimate for the cause of death mentioned in the story.

(3) The effect of the story could also generalize to other risks according to their similarity to the risk described in the story. Hence, a story about a leukemia victim, for example, will be expected to have (a) a considerable effect on the estimated frequency of other cancers, (b) a weaker effect on the estimated frequency of other diseases, and (c) little or no effect on the estimated frequency of unrelated risks, e.g., tornado or plane



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Figure 1: Additive tree representation of risks used in Experiment 1.



crashes. This hypothesis, (which appeared to us most probable) is suggested by the classical notion that the gradient of generalization is determined by the similarity between the critical stimulus and the target.

(4) The story could produce a global effect, that is, an increase in the judged frequency of both related and unrelated risks. There is evidence in the social psychological literature that changes in affect could influence a wide range of unrelated behaviors and judgments such as the frequency of helping (Isen & Levin, 1972), and the evaluations of the performance of household appliances (Isen, Shalke, Clark & Karp, 1978). For a review of some of the relevant literature see Clark & Isen (1982).

Thus, we consider four possible effects of the exposure to an affect-arousing story: (1) no increase in fatality estimates, (2) a local increase, limited to the target risk, (3) a generalization gradient, and (4) a global increase. The four possible effects are not necessarily incompatible; both local and global increases could be found in the same set of data.

#### The Set of Risks

In order to generate a set of risks for the present studies we asked a group of 68 undergraduates from Stanford University to list the major risks, including diseases, accidents and disasters, that are important causes of death in the U.S. Of the 36 risks listed by the subjects, we selected a set of 18 risks that were either the most frequent causes of death, or listed most frequently by the subjects.

To ascertain the perceived structure of these risks, we presented all pairs of 18 risks to 110 subjects recruited through an advertisement in the University of Oregon student newspaper. They were asked to rate the similarity between risks on a scale from 1 (low similarity) to 10 (high similarity). Three groups of subjects each rated one-third of the total of 153 pairs. The average similarities between risks were analyzed using the ADDTREE algorithm (Sattath & Tversky, 1977). The resulting tree representation of the proximity among the 18 risks is shown in Figure 1.

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Figure 1 about here.

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In an ADDTREE (or additive tree) representation, the objects (risks) appear as the terminal nodes of the tree, and the distance between objects is the length of the horizontal part of the path that connects them. (The vertical part is included for graphical convenience.) Thus, leukemia is close to stomach cancer, less close to stroke and quite distant from war

and from terrorism. The length of each horizontal link in the tree can be interpreted as the measure of the set of features that are shared by all objects that originate from this link. Hence, the terminal links represent the unique features of the respective objects, while the non-terminal links correspond to the clusters induced by the judged similarities. A suggested interpretation of these clusters, or links, is provided by italicized labels. For a discussion of tree and other representations of risks see Tversky and Johnson (Reference Note 1).

The tree displayed in Figure 1 fit the judged similarities quite well: the product moment correlation between them is .92. It also yields several distinct and interpretable clusters including diseases, violent acts, and hazards. To study the impact of mood on risk estimates, we selected one risk from each of these clusters (leukemia, homicide, fire) as target risks and constructed a newspaper-like account for each. We have also identified the two nearest neighbors of these risks as near-target risks. In Figure 1, the three target risks are underlined and the respective near-target risks are starred.

Our first study includes three experimental groups, each of which read a single story about a death caused either by leukemia, homicide or fire. The fourth group served as control and did not read stories related to death. Each experimental condition contained three types of risks: the target (described in the story), the near-target (its two closest neighbors), and the non-target risks (the remainder).

## Experiment 1

### Method

#### Subjects.

Seventy-two paid subjects, about equally divided between men and women participated in the experiment. They were recruited through an advertisement placed in the University of Oregon newspaper, and run in moderate sized groups in a classroom setting. Subjects completed the two relevant questionnaires along with several other unrelated experimental tasks.

**Procedure.**

In the first questionnaire, entitled "Newspaper Reporting Study", the subjects were given the following instructions.

"A recent trend in journalism has been the increase of personal interest and feature stories...describing both good news such as personal successes, as well as accounts of death and disaster."

The subjects read a few stories of this type and rated each story on a 9 point scale with respect to interest and quality of writing. They indicated how they would feel if they had read the story in their local newspaper on a (9 point) mood scale ranging from "positive, uplifted" to "negative, depressed" This last scale served as a manipulation check.

All four groups were presented with two brief and mundane items, which were two paragraphs long, modeled after "People in the News" columns in local papers.

The three experimental groups each received an additional story about the death of a single person. The experimental stories that describe the fatal events consisted of three paragraphs. The portrayal of the death was detailed, designed to induce anxiety and worry. The victim in each case was a young male, who appeared to be an unsuspecting normal undergraduate prior to the onset of the fatal event.

Following the completion of this questionnaire, the participants were presented with a second booklet entitled "Perception of Risk Questionnaire", containing the dependent measures. In the first part of this questionnaire, the subjects were asked to express, on a 9 point scale, their level of worry and concern for each of the 18 causes of death. In the second part, the subjects were asked to estimate the frequency of various fatalities. As in the study of Lichtenstein et al. (1978), subjects were told that each year about 50,000 people in the United States die in motor vehicle accidents. They were then asked to estimate the number of annual fatalities due to each of the remaining 17 causes of death. They were urged to be as accurate as they could and to check their answers for consistency.

**Data Analysis.**

The frequency estimates spanned several orders of magnitude, producing very skewed distributions. Consequently, all observed estimates were subjected to a logarithmic transformation, yielding approximately normal distributions. Note that the mean of the transformed values is the logarithm of the geometric mean.

All the experiments reported in this paper utilize a similar design. The stories represent a between-subjects factor, while the risks are a within-subjects factor. Significance tests were performed using the subjects factor as the error term for the story effect, and the

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**Table 1:**  
 Ratios of Experiment to Control Means<sup>1</sup>  
 for matched and non-matched stories, Experiment 1

Type of Risk	Risk	Matched Story	Non-Matched Story	Mean
Target	Leukemia	3.52	3.65	4.20 (Diseases)
Near-Target	Lung Cancer Stomach Cancer	3.45	5.02	
Non-Target	All Other Risks	1.37	1.55	1.49
Target	Fire	.94	1.50	1.51 (Hazards)
Near-Target	Electrocution Lightning	1.34	1.75	
Non-Target	All Other Risks	1.52	1.97	1.67
Target	Homocide	1.22	1.16	1.41 (Violence)
Near-Target	War Terrorism	.75	1.91	
Non-Target	All Other Risks	2.88	1.53	1.97

<sup>1</sup>Means are geometric

subjects by risk by story interaction for the effects of risk and the risk by story interaction.

## Results

### Manipulation Checks.

As expected, the stories presented to the experimental groups were judged more depressing than the filler stories. The means of the two filler stories were 4.27 and 5.67 on the nine point scale, while the means of the critical stories were 6.90 for the leukemia story, 6.89 for the fire story and 7.12 for the crime story. This comparison of filler vs. critical stories is significant by an a priori comparison  $F(1, 120) = 114.6, p < .001$ .

### Worry Scales.

The stories were also effective in raising the level of concern for various causes of death: in each condition the mean of reported worry increased relative to the control (mean increase = .75 scale unit). Of a total of 54 comparisons (3 conditions by 18 risks) between the experimental and control groups, 46 were higher in the experimental group. The increase in worry, however, was not related to the target risk, or to the match between the assessed risk and the risk mentioned in the story.

### Frequency Estimates.

Our major dependent measure, the frequency estimates, reveals a strong global increase. Of 51 comparisons (3 experimental groups with 17 risks each) 41 show increases relative to control. Overall, the frequency estimates of the three experimental groups were 74 percent higher than those of the control groups. The crime account was the most effective of the three stories, increasing estimates by an average of 133 percent. The leukemia and the fire account increased the average estimate by 56 and 50 percent, respectively.

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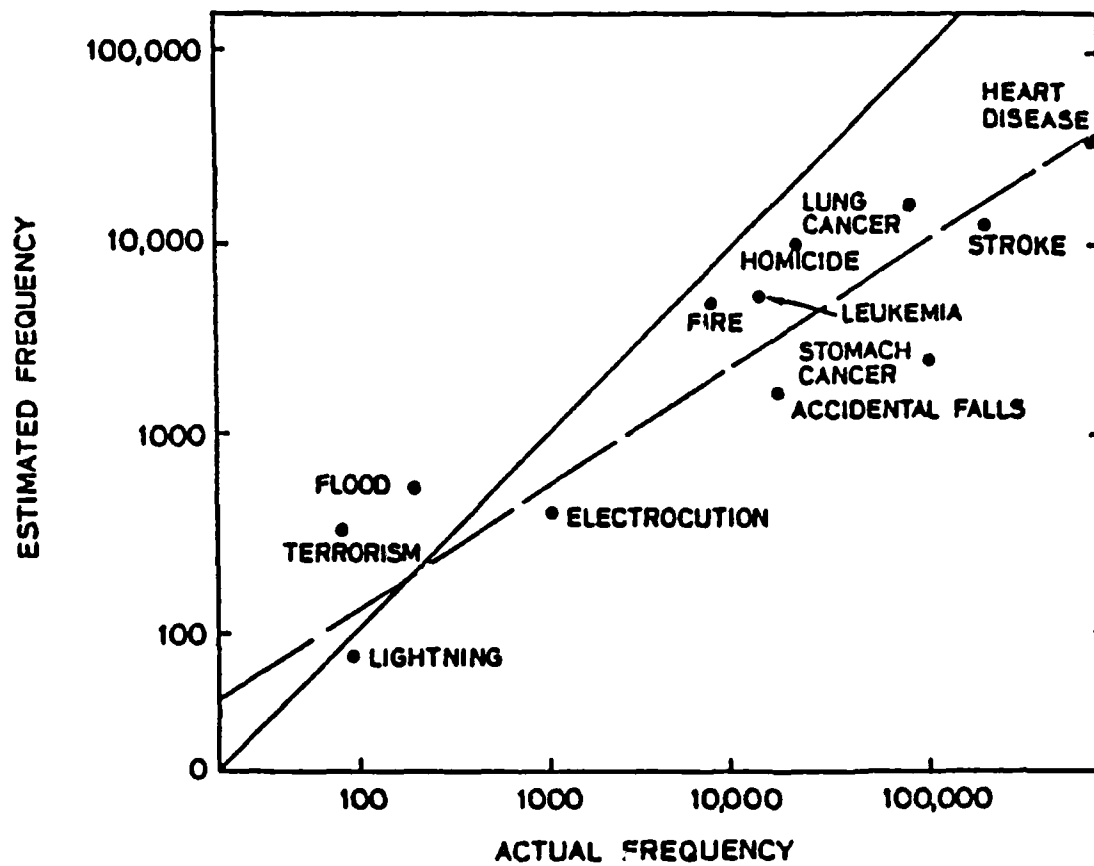
Table 1 about here.

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To test for a local effect, in the presence of a global effect, we compared the estimate of each target risk across each of the three experimental conditions. A local increase implies a larger increase for targets when they match the topic of the story than when the story and target do not match. Gradient generalization implies, in addition, a larger increase for the near-target risks when they match the topic of the story. Table 1 presents the ratios of the geometric means of the experimental estimates to the geometric means of the control estimates for target, near-target and non-target risks when matched and not

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Figure 2: Subjective vs. objective estimates of frequency.  
Experiment 1.



matched by the story. Note that this ratio is higher in the unmatched condition than in the matched condition for leukemia and fire, contrary to the prediction of the local and gradient hypotheses. For crime, the reverse is true, but the effect does not approach statistical significance by an a priori contrast  $F(1, 1474) = 0.10, p > .50$ . Thus, there is no evidence of either a local or gradient effect.

These conclusions are confirmed by the results of an analysis of variance. The a priori contrast of the three experimental groups to the control is significant,  $F(3, 69) = 2.76, p < .05$ , but the overall effect of the story by risk interaction is not,  $F(48, 1078) = 1.04, p > .40$ .

To obtain an alternative test of the gradient hypothesis that does not depend on the choice of near-target risks, we correlated, for each experimental story, the change in risk estimate (relative to control) induced by that story with the similarity of each risk to the target of that story. The gradient hypothesis implies a positive correlation between the magnitude of the effect and the similarity to the target. The product moment correlations were  $-.06, -.32,$  and  $.21$ , for fire, crime, and leukemia respectively, none of which are significantly different from zero.

Although we found no significant differences among the experimental stories, we found sizable differences among the risks. Table 1 shows that, on average, negative mood induces a larger increase for estimates of diseases than for hazards and for violence, a pattern confirmed by a post-hoc comparison,  $F(2, 1078) = 4.23, p < .05$ .

#### Accuracy of Estimates.

As a sidelight, it is interesting to examine the accuracy of the subjects' estimates. Figure 2 plots the available statistical estimates for 13 of the 18 causes of death against the values estimated by the control group, along with the best fitting linear regression line. The correlation between the subjective and the objective values is  $.48$ . Figure 2 reveals a strong tendency to underestimate large risks and a weak tendency to overestimate small risks. Because the current set of risks included fewer extremely rare causes of death (less than 100 fatalities a year), than the study by Lichtenstein et al. (1978) the overestimation of infrequent risks is less pronounced in our data. For similar reasons, the regression of subjective against objective estimates is fairly linear in the present study and quadratic in the study of Lichtenstein et al.

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Figure 2 about here.

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**Discussion.**

Much to our surprise, we found a large global increase in estimated frequency but failed to detect either local or gradient effects. The story influenced the estimates for the entire group of risks regardless of the similarity between the estimated risk and the topic of the story.

Experiment 2 was designed to obtain local and gradient effects by constructing a more sensitive test. First, we added a new task which requires the subjects in each condition to rank the risks with respect to the number of fatalities. This procedure induces a direct comparison between target and non-target risks which does not require numerical estimates of frequency. Second, we reduced the set of risks to seven, the three target risks, each target's most similar (near-target) risk from Experiment 1, and one non-target risk. A local or a gradient effect may be more pronounced when the task is made simpler by reducing the number of estimates. Third, we strengthened the experimental manipulation by placing the stories and the frequency estimates in the same questionnaire. Finally, we increased the statistical power of the test by doubling the total number of subjects.

**Experiment 2****Method****Subjects.**

A new group of 182 subjects were recruited through an advertisement placed in the University of Oregon newspaper. As in Experiment 1, they completed several unrelated tasks along with the current questionnaire.

**Procedure.**

The three experimental groups received the two filler stories plus one of the critical accounts from Experiment 1. As before, they rated the stories for interest, quality of writing, and the mood evoked. The control group did not read these accounts and proceeded to the next section of the questionnaire.

All groups then ranked the seven risks, in terms of the likelihood that the risk would be the cause of their own death. Afterwards, they were given the same instruction as in Experiment 1 and asked to estimate the frequency of deaths for the seven causes.

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**Table 2:**  
Ratios of Experimental to Control means<sup>2</sup>  
for matched and non-matched stories. Experiment 2

Type of Risk	Risk	Matched story	Non-Matched story	Mean
Target	Leukemia	2.70	2.49	2.23 (Diseases)
Near-Target	Lung Cancer Stomach Cancer	2.29	1.95	
Non-Target	All Other risks	1.45	1.49	1.48
Target	Fire	1.62	3.02	1.84 (Hazards)
Near-Target	Electrocution Lightning	1.13	1.65	
Non-Target	All Other Risks	1.17	1.34	1.28
Target	Homocide	2.38	1.31	1.15 (Violence)
Near-Target	War Terrorism	1.16	.76	
Non-Target	All Other Risks	2.83	1.64	1.87

<sup>2</sup> means are geometric

## Results

### Manipulation Checks.

Again, the stories effectively induced a negative mood. The means on the mood scale (6.82 for crime, 6.67 for leukemia and 6.63 for fire) were higher than the values for the filler stories and close to the corresponding values obtained in Experiment 1.

### Ranking of Risks.

An examination of the mean rank in each condition shows no tendency to assign a higher rank to a risk when it matches the topic of the story than when it does not. For leukemia, the matched story produced a .30 decrease in mean rank. When matched by the story, fire and street crime show increases of .50 and .22 respectively, but neither is statistically significant. The risk by story interaction, which should reflect a local or generalization effect does not approach significance,  $F(18, 1092) = .71$ ,  $p > .50$ . Furthermore, the a priori contrast comparing the target's rankings in the control to the targets rankings in the appropriate experimental condition, is also not significant,  $F(1, 1092) = .01$ ,  $p > .50$ . Ranking data, of course, do not provide a test of a global effect.

### Frequency Estimates.

Again the results show a global increase and no evidence for a local increase or for a generalization gradient. The crime story was the most effective, raising the mean estimate 144 percent, followed by the leukemia story which raised the estimates by 73 percent. The fire story was the least effective showing an overall increase of only 14 percent. The experimental group estimates were larger than the control groups for 19 of the 21 comparisons.

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Table 2 about here.

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Table 2 presents the ratios of the geometric means of experimental to control estimates for target, near-target and non-target risk estimates. Recall that a local effect implies that the ratio is higher when the target matches the topic of the story than when it does not. This pattern appears to hold for leukemia and crime while fire reveals the opposite pattern. Closer examination shows that the effects for leukemia is far from significant. Although crime produces a substantial effect, the increase is due to the greater effectiveness of the crime story. As seen in Table 2, the non-target risks show larger increases (2.83) than either the target (2.38) or near-target (1.16) risks. An a priori contrast comparing the increase in the target does not differ from the overall increase,  $F(1, 1083) = 1.15$ ,  $p > .30$ .

An analysis of variance confirms the effect of the three stories: the main effect of story is significant,  $F(3, 182) = 4.11, p < .01$ , as is the contrast comparing the control to the three experimental groups,  $F(1, 182) = 5.86, p < .025$ . The lack of local and gradient effects is again demonstrated by the insignificant risk by story interaction,  $F(18, 1083) = .80, p > .65$ .

Table 2 also shows a differential mood effect on the various risks. In particular, the impact of the stories is largest for diseases as in Experiment 1, smallest for violence and intermediate for hazards. This ordering is significant, as shown by a posthoc contrast,  $F(2, 1083) = 9.85, p < .001$ . Evidently, estimates of diseases tend to be more volatile than estimates of other risks.

### Discussion.

The major conclusion of these analyses is the robustness of the global increases in perceived frequency of death. Several changes in the experimental procedure designed to induce a local effect did not produce the expected result. These data demonstrate that bad mood created by brief stories have pervasive global effects on estimates of fatalities. However, we have found no connection between the information contained in a story and its impact on the estimated frequency of death. The overriding factor in these increases is not the story told, but rather the mood it induces in the reader. Hence, it is natural to inquire whether a sad story, unrelated to risk, would also increase estimates of fatality, and whether the effect of the present stories extends to the judged frequency of undesirable events that do not introduce the risk of death. In the next experiment we include a non-risk story and extend the list of estimates to include non-fatal events like damage from floods and adverse life events such as divorce and bankruptcy.

### Experiment 3

#### Method

#### Subjects.

One hundred and ninety-one students in an introductory Psychology class at the University of California, Berkeley completed this questionnaire, along with several others at the beginning of a regularly scheduled class meeting. Eight subjects were discarded from the analysis because of incomplete data or nonsensical responses.

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Table 3: Ratios of Experimental to Control means.<sup>3</sup>  
Experiment 3

<u>Type of Risk</u>	<u>Story</u>		<u>Mean</u>
	<u>Crime</u>	<u>Depression</u>	
Fatal Risks	1.30	1.23	1.27
Non-Fatal Risks	1.73	1.63	1.65
Life Problems	2.63	2.82	2.75

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<sup>3</sup> means are geometric

**Procedure.**

Experiment 3 used the "Newspaper Reporting Study" questionnaire, which required subjects to read several stories, and rate them on three scales. The control group received the two filler stories used in Experiment 1. There were two experimental groups: One read the crime story which was the most effective in the two previous studies. The second read a depressing story unrelated to risk. The story described several unfortunate events which occurred to a young male who had just broken up with his girlfriend, was under stress at his job, and was further pressured by his family.

Upon completion of the "Newspaper Reporting Study," subjects received a "Perception of Risk" questionnaire in which they were asked to estimate the frequency of some 21 undesirable events. The instructions and the format were the same as in Experiment 1. The list included, in addition to the seven risks from Experiment 2, two new types of events. The first involves non-fatal risks, that is, the number of people who suffer, but not necessarily die, from various causes. The second involves events, not normally viewed as risks, that have a negative impact on the quality of life. The entire set of events used in this study is presented in the left hand column of Figure 3. Thus, Experiment 3 extends our previous studies by using a non-risk story and by investigating non-fatal events.

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Table 3 about here.

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**Results****Manipulation Checks.**

The depression story was as effective as the crime story in inducing negative affect: the means on the mood scale were 6.92 and 6.93, respectively, which are comparable to the results of the first two studies. The mean for the filler stories in the control group was 5.42. The differences between the means are highly significant by an a priori contrast of the experimental groups to the control,  $F(1, 183) = 31.61, p < .001$ .

**Frequency Estimates.**

The street crime and the depression stories increased the judged frequencies by 76 and 75 percent respectively. An analysis of variance confirms the main effect of story,  $F(2, 183) = 3.06, p < .05$ , and the pattern of the increases is quite similar in the two experimental groups. There was no hint of a local increase or a generalization gradient. For example, the increase in the estimated frequency of crime and chronic depression, which could be considered the matched risks for the two stories, are not significantly

different.  $F(1,3575) = 0.01$ , and  $F(1,3575) = 0.69$  both  $p > .40$ . Again, it appears that negative mood increases the judged frequency of negative events, regardless of the relation between the content of the story and the estimated quantity.

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Table 3 about here.

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Table 3 displays, for each story, the ratio of the experimental group geometric means of experimental to control estimates for each type of event. The table indicates that the magnitude of the mood effect varies for the three types of event. Life problems yielded larger ratios than did non-fatal risks, which in turn, were larger than the ratios for the fatalities. This is confirmed by a post-hoc contrast,  $F(2,3575) = 11.81$ ,  $p < .01$ .

The finding that negative mood increases risk estimates, independent of the relation between the risk and the story, suggests that positive mood could produce a similar global reduction in risk estimates. This hypothesis is tested in our last experiment.

#### Experiment 4

##### Method

##### Subjects.

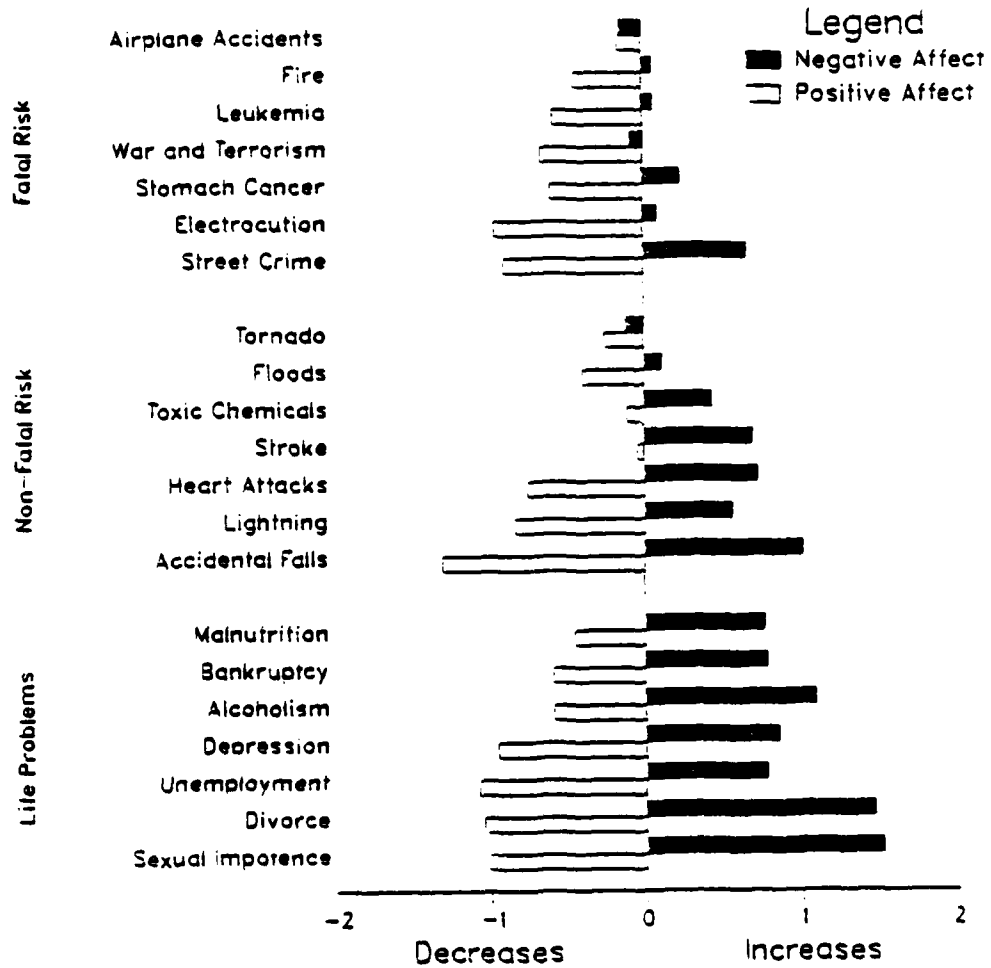
A total of 108 subjects participated in this experiment. Eighty-eight were recruited through signs placed on the Carnegie-Mellon University campus. The subjects were paid for their participation in the study, which included several additional experimental tasks. An additional 20 subjects were undergraduates who completed the questionnaire at the beginning of regularly scheduled class meetings.

##### Procedure.

The study was similar to Experiment 3, but used a single experimental group who read a story designed to produce positive affect. It described a series of fortunate events occurring to a young male, including admission to medical school, and success on a difficult exam.

# Affect and the Perception of Risk

Figure 3: Increases and decreases (log scale in estimated frequency, relative to control, induced by positive or negative affect for each of 21 risks.





## Results

### Manipulation Checks.

The positive story shows a significant decrease in reported worry compared to the control, 5.56 vs. 4.70. This effect is significant  $F(1,110) = 12.25$   $p < .001$ .

### Frequency Estimates.

Positive mood resulted in lower estimated frequencies for 20 of the 21 estimates. The average decrease was 89 percent, which is comparable in magnitude to the increase in estimates caused by the negative story. An analysis of variance confirms the significance of the effect of the story,  $F(1,106) = 5.779$ ,  $p < .01$ , and the lack of an interaction between story and risk,  $F(20, 2120) = 1.06$ ,  $p > .60$ .

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Figure 3 about here.

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Figure 3 displays the difference (in log units) between experimental and control estimates for the 21 events estimated in Experiments 3 and 4. The data from Experiment 3, which induced negative mood is shown by black horizontal bars and the data from Experiment 4, which induced positive mood is shown in white. If the mood manipulation had no effect, the bars would vanish, representing no change in the estimates.

Figure 3 highlights the effectiveness of the manipulation of mood. With few exceptions the black bars are to the right of the zero line representing increases in estimated frequency while the white bars are to the left, representing decreases. Furthermore, Figure 3 reveals that the effect of mood, both positive and negative, tends to be larger for life problems than for fatal and non-fatal risks. Note that the life problems used in this study are generally more frequent than the risks. The data in Figure 3 suggests the hypothesis that frequent events are more labile than less frequent events. This hypothesis is consistent with the results of Experiments 1 and 2 where the most frequent causes of death, diseases, were more susceptible to the experimental manipulation than other risks.

To explore the relationship between perceived frequency and lability of estimates, let  $X_i$  and  $C_i$ , respectively, be the geometric means of the estimated frequency of event  $i$  in the experimental and control groups. The ratio  $E_i = X_i/C_i$  measures the effect of the experimental manipulation. The correlation between  $E_i$  and  $C_i$  across all events is .74 for Experiment 3 and -.46 Experiment 4.

Note that a proportional increases or decreases in frequency estimates as a consequence of a mood effect should produce a correlation of 0 between  $C_i$  and  $E_i$ . The presence of

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Table 4: Percentage of Subjects Increasing Estimates for Risks that Match and do not Match an Underestimated Target.

Underestimated Risk	Estimate Type	Matched	Non-Matched
Leukemia	Near-Target (Lung Cancer Stomach Cancer)	72	13
	Non-Target (All others)	19	23
Fire	Near-Target (Lightning Electrocution)	51	10
	Non-Target (All others)	31	17
Crime	Near-Target (War Terrorism)	60	22
	Non-Target (All Others)	16	25

substantial positive and negative correlations indicates that the impact of mood is larger than predicted by a proportional effect. Other variables besides perceived frequency, such as knowledge, ambiguity, and the nature of the risk, can undoubtedly influence the volatility of the estimates. The investigation of these factors requires a design in which (perceived) frequency of risk is not confounded with these factors.

### General Discussion

The results of the preceding studies demonstrate that mood induced by brief reports has a large and pervasive impact upon estimates of the frequency of risks and other undesirable events. Furthermore, the effect is independent of the similarity between the story and the risk. The latter result contrasts sharply with the typical finding that the degree of generalization is largely determined by similarity. For example, we have obtained a highly ordered generalization gradient over the set of 18 risks from Experiment 1, using a conditional revision procedure (Tversky & Johnson, Reference Note 1). In this study, subjects first estimated the frequency of death due to the 18 risks. They were then told to assume that they had underestimated a particular target risk and asked to indicate the other estimates that they would increase given this information. The gradient hypothesis implies that the more similar, near-target risks, will be revised more often than the unrelated, non-target risks. Table 4 summarizes the test of this hypothesis for the three target risks used in Experiments 1 and 2. The matched column presents the percentage of subjects who increased their estimates of near-target risks. The non-matched column presents the percentage of subjects who increased their estimates for the corresponding risks when they do not match the target. Table 4 shows a small overall increase for non-target risks, and a large increase in the matched near-target risks. These results reveal a small global effect and a strong generalization gradient. Evidently, the effect of the information provided by the stories in Experiment 1 and 2 was different than the effect of the information that a particular risk was underestimated. The former produced a large global effect, while the latter yielded the expected gradient of generalization.

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Table 4 about here.

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The pervasive global effect of mood and the absence of a local effect pose a serious problem to memory-based models of this effect, such as spreading activation within a semantic network. In such models, the impact of an experience is largely determined by the strength of association between the input (e.g., the story) and the target (e.g., the risks). Risks that are closely linked to the story should be influenced more than unrelated risks, contrary to the present findings. The novel aspect of these results is not the global mood effect, which has been observed by several investigators, (see, e.g. Bower 1981, Bower &

Wright, Note 2; Feather, 1966, Clark & Isen, 1982) but rather the presence of a pervasive global effect in the absence of any local effect of similarity or association. This combination is particularly surprising because the effect of mood was produced not by an arousing experience but rather by a brief mundane account of a specific event. Evidently, people dissociate the affective impact of the account from its content. These observations are consistent with the view that the influence of affect is at least partially independent of semantic association (Zajonc, 1980). The results give rise to the hypothesis that we tend to make judgments that are compatible with our current mood, even when the subject matter is unrelated to the cause of that mood. If we attend the theater in a bad mood, for example, we are likely to be critical of the play, and while we do not normally attribute our mood to the play, we often attribute to the play characteristics that could have produced our current mood.

This hypothesis suggests that people are often not aware of the linkage between the stimulus that induces the mood and the response it elicits even when they know of the cause of the mood, and are aware of its effects. Although we know that a bounced check may put us in a bad mood, which in turn can make us short tempered, we rarely attribute a refusal to help a friend to a bounced check. When such attributions are made, they are usually limited to events which are similar to the cause of mood. Financial difficulties may explain why a new bill is particularly annoying, but they are rarely used to explain cynical responses to a colleague's suggestion.

A post experimental questionnaire which followed Experiment 3 supported these hypotheses. Only 3 percent of the experimental subjects ( $n = 67$ ) acknowledged the possibility that the depressing story influenced their estimates of fire or leukemia, although 50 percent agreed that the story influenced their mood, and 40 percent of the control subjects ( $n = 57$ ) agreed that a negative mood could affect estimates of unrelated risks. Hence subjects acknowledged both the effect of the story on their mood, and the effect of mood upon their estimates, but they did not link the cause of their mood to its subsequent effect. The responses of the (experimental) subjects also showed that awareness of the effects of mood is enhanced when the cause of the mood (i.e., the story) matches the relevant judgment. While 40 percent of the subjects thought that the depressing story had changed their estimate for depression, only 14 percent thought it had changed their estimate for street crime. In reality the critical story had an equally pronounced effect for both related events, such as depression, and unrelated events, such as street crime or toxic chemical spills.

The interpretation of public perception of the threat and the prevalence of risks should take into account the susceptibility of lay judgments to manipulations of mood, and the apparent lack of awareness of this effect.

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