Warnings, Terrorist Threats and Resilience: A Laboratory Experiment

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Abstract: One of the main goals of terrorism is to instill fear in a targeted populace. We investigate how information precision about rare, but highly devastating terrorist attacks influences psychological resilience, which we operationalize as the ability to continue to take optimum risks. First, we develop a mathematical model of a citizen's resilience in the face of a terrorist threat. We then test the model in a laboratory experiment in which individuals face a choice between lotteries that offer higher payoffs, but have a small probability of a large negative loss and a safe option. In the experiment, we vary the nature of warnings about the lotteries to see how vague warnings versus precise information influence optimal risk-taking (resilience). We find that precise information increases subjects' willingness to take risks. Warnings containing no information do not influence subjects' willingness to accept risk, but can influence resilience through affecting which risks subjects take.

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I. Introduction

A common understanding of terrorism is that it is the premeditated use or threat to use violence conducted by non-state actors, involving multiple objectives with political/social motives (e.g., Enders and Sandler, 2006). While the immediate consequences of a terrorist attack may involve loss of life or serious injury (particularly of noncombatants – one of the defining features of terrorism as opposed to other kinds of armed conflict), these are merely immediate targets of an otherwise multi-pronged strategy. The effect of terrorism is meant to be bigger than the sum of the casualties an event inflects. Of greater importance than the immediate impact is the fear and panic it produces in a targeted populace. Terrorism is a form of psychological warfare. According to Fischhoff (2006) terrorists seek to disrupt normal life, alienating people from their leaders and turning citizens against one another. However, fear and panic are not constant across all victims and targets of threatened or attempted terrorist attacks. During a crisis, research has shown (e.g., Glass, 2001), people respond reasonably, however their actions may be ineffective if they act on the basis of poor information. Two questions are, 1) why do some individuals manifest significantly higher resilience in the face of terrorist threats? 2) Can the government increase psychological resilience of the public? Central to this study is how government-supplied information about the risk posed from terrorism influences public resilience.

Since the events of 11 September 2001, most politicians and homeland security agencies have focused on resilience in terms of infrastructural concerns, i.e., the continued functioning of the public and private sector post-attack.[i] Terrorism has a measurable negative effect on economic activity (e.g., Abadie and Gardeazabal, 2003, and Gaibulloev and Sandler, 2011). Further research suggests that successful attacks may also have an indirect negative economic effect by eroding trust within affected societies (Blomberg, Hess, and Tan, 2011). Thus, while it is understood that terrorism has direct and indirect negative impacts on economic activities, what remains poorly understood is *psychological* resilience—how an individual, group, or community can adapt and continue to function in the face of a terrorist threat.

We define psychological resilience as an individual's willingness to continue to take risks when under threat of terrorism that are positive in expectation, but have a small chance of a large negative shock. This is closely related to the definition of resilience offered by Tugade, Fredrickson, and Barrett (2004) as "the ability to bounce back from negative events." For instance, an individual may ride a commuter train to work every day. In the face of a terrorist threat, they may choose to stay at home or take their own car at greater expense to them and society. However, they may show resilience by continuing to ride the train. The ability to take these small, everyday risks in the specter of terrorism is how we define resilience, and serves as the basis for our laboratory experiment. Some might question the external validity of resilience via transportation choices. However, as Klar et al. (2002) and Bar-Tal and Sharvit (2008) demonstrate, this trade-off in transportation occurred in Israel at the height of the 2nd Intifadah.

Our experiment addresses the central question faced by governments in communication to their citizens about the nature of terrorist threat. How much information do they give and of what nature? We examine the trade-off between vague warnings versus precise information on risk-taking (resilience). This echoes work in psychology and economics on the interplay between ambiguity and risk aversion (Fox and Tversky, 1995; Epstein, 1999). Do vague warnings lead individuals to be less willing to take risks (ambiguity aversion)? Given the criticism of previous US government terrorist warning systems[ii] efforts to understand how individuals parse government information (or lack thereof) in warnings is crucial.

Greater knowledge of resilience and its determinants is important, especially for government agencies responsible for not only communicating risk or threat of attacks to a worried public, but also in reassuring the public through public service announcements. Striking the right balance between vigilance, and avoiding the unnecessary spread of panic, all while maintaining the public's attention is a difficult task and central to issues of resilience. Terrorism generally has a small direct effect (e.g., causalities and infrastructure damage), but a large indirect effect (creation of fear). Understanding how individuals' decisions change as the government releases warnings and/or precise, actionable information about low-probability, highly adverse events is central to understanding resilience.

We develop a mathematical model of how a representative citizen's behavior changes with respect to government warnings about a terrorist attack. The model shows that the citizen's resilience, as represented by her willingness to take risks, increases with the precision of the government's message. Meanwhile, vaguely worded warnings devoid of information should have no effect. We then test the model in a decision theoretic lab experiment where subjects choose between two risky, but more profitable choices and a lower paying safer option. We do find that resilience increases when subjects are given precision information about the lotteries. Vague warnings have no effect on subjects' willingness to take risks compared with releasing no information at all. However, vague warnings can influence which risks subjects find acceptable.

The paper proceeds as follows. In Section II, we discuss some of the relevant literature from psychology and political science on terrorism, risk, resilience, and decision-making. Section III presents the theoretical model. Section IV describes the experiment before we present the results in Section V. Finally, in Section VI, we offer some conclusions and policy implications of our research.

II. Literature Review

Our research on resilience connects three strands of extant literature: (1) the effect of violence and terrorism on individual and political behavior, (2) the role of risk in decision-making, and (3) how habits and conditioning influence behavior.

Studies investigating the effect of violence on individual behavior have been mixed in their conclusion. Some research point to the negative effects of violence: increased levels of post-traumatic stress [PTSD] and anger and higher levels of ethnocentrism (Jakupcak, Conybeare, Phelps, Hunt, Holmes, Felker, Klevens and McFall, 2007; Palmieri, Canetti-Nisim, Galea, Johnson and Hobfoll, 2008; Canetti-Nisim, Halperin, Sharvit and Hobfoll, 2009). Shahrabani, Benzion and Shavit (2009) show that recalled emotions about exposure to terrorism lead to higher levels of negative emotions. Other studies suggest the potential for positive effects of exposure to violence: greater ingroup cohesion and higher levels of political participation (Blattman, 2009; Gilligan, Pasquale and Samii, 2010).

Previous research has shown that the level of exposure to terrorism influences citizens' attitudes towards the perpetrators (the terrorists), and towards their own leaders. Gould and Klor (2010) find that higher levels of terrorism lead to a greater willingness to compromise with the terrorist demands up to a point, past which increases in terrorism lead to a hardening of citizen's opinions towards terrorists. The anxiety and fear caused by terrorism also have an impact on voters' appraisals of their leaders. Mueller (1970) documents a rally 'round the flag effect, whereby leaders enjoy a boost in popular support during periods of crisis or conflict. Using survey evidence after the 2004 Madrid train bombings, Bali (2007) shows citizens are more engaged politically following an attack, and that the rally 'round the flag effect may be reversed if citizens blame the incumbent leader for the attack. Furthermore, in times of threat, citizens value leadership more than in less tense times (Merolla and Zechmeister, 2009), suggesting that risk perceptions may influence the political behavior of both citizens and politicians.

Risk is thought to be central in how individuals process information about threats such as terrorism. Kahneman and Tversky (1979) in their landmark work on Prospect Theory propose that individuals are more likely to be risk-accepting in the domain of losses, and risk averse in the domain of gains. The difference between risk (knowing the underlying probability and gains and losses) and uncertainty (not having access to this information) can greatly affect individuals' decisions (Hau, Pleskac and Hertwig, 2010). Individuals have been shown to also exhibit ambiguity aversion, a dislike of making decisions in which they are uncertain of the outcome (Fox and Tversky, 1995).

Citizen's reactions are partially based on their degree of habituation with a given level of threat (Ferster and Skinner, 1957). With respect to terrorism, Yechiam, Barron and Erev (2005) examine the effect of exposure to rare negative events and risky-behavior. Using data on hotel stays of foreign tourists and Israeli tourists within Israel, they find that Israeli tourists are less sensitive to terrorism than foreigners who have less experience with such threats. Furthermore, they use a laboratory experiment to show that sensitivity to low-risk, but highly negative shocks are strongly influenced by familiarity and experience.

Fischhoff (2006) points out that communicating effectively about terror risks is an important counterterrorist strategy. He suggests three tasks for the government: 1) Have a credible message to communicate; 2) Create appropriate communication channels and 3) Deliver decision-relevant information, concisely and comprehensibly. Likewise, Freedman (2005, p. 408) argues that "vague and general exhortations to be alert and vigilant tend to be disregarded." However, the now-defunct color-coded Homeland Security Advisory System (HSAS) provided only warnings and not actionable information, confusing both citizens and government agencies (Shapiro and Cohen, 2007).

The previous studies suggest that citizens' responses to terrorism are influenced by both experiential factors, perceptions of risk, and appraisals of political leaders. Yet there remains a gap in the extant literature in how different levels of information and different types of warnings influence responses to low probability, highly negative shocks.[iii] We attempt to fill this gap by developing a formal model of risk-taking in the shadow of terrorist attacks (Section III) and then experimentally testing the model.

III Theoretical Model

In the model a terrorist organization may attack infrastructure and terrorize the population, and this can make individuals change their behavior due to fear of future attacks. The representative agent is a citizen that may have his behavior and habits affected by a terrorist attack. The government is an exogenous agent that aims at maintaining normalcy [resilience] even in the event [or threat] of a terrorist attack. We follow Fischhoff (2006) and assume that Government messaging to managing terror risks will influence public behavior, increasing resilience. In our set up, the government exogenously decides which message in terms of the content, *G*, to send, and then the citizen and terrorist react to it, choosing their current behavior, *X*, and whether to attack or not, *A*, respectively.

Variables: X = current (normal) citizen behavior; H = habits of the citizen; A= terrorist attacks; r= citizen's rate of time preference; F = infrastructure; G = government messaging.

The problem of the representative citizen is to maximize her utility through routine behavior X when facing the possibility of terrorist attacks, A, subject to the evolution of her own behavior, infrastructure, and terrorist attacks. The habits of the citizen H evolves over time , $\dot{H} \equiv dH/dt$, according to the habit formation process[iv] described in Equation (1). Habits change when current citizen behavior differs from what the citizen has being doing habitually. The time evolution of physical infrastructure, $\dot{F}$, given by Equation (2), is affected by terrorist attacks, by the existing infrastructure, and by government messaging. Equation (3) describes the time evolution of terrorist attacks, $\dot{A}$; it is assumed that they evolve as a function of past terrorist attacks, infrastructure, and government messaging. In Equations (2) and (3), government messaging has the important role of keeping the citizen's behavior as normal as possible, i.e., it ensures normalcy even in the event of destruction of infrastructure caused by a terrorist attack.

$$\underset{X}{Max}\int_0^{\infty} U(X,H,A)\exp(-r\,t)dt$$

$$\dot{H} = a(X - H) \ (1)$$

$$\dot{F} = f(A,F,G) \ (2)$$

$$\dot{A} = g(A,F,G) \ (3)$$

The citizen's instantaneous utility function U and has the following characteristics: $U_X > 0, U_{XX} < 0; U_H < 0, U_{HH} > 0, U_A < 0, U_{AA} > 0, U_{HA} > 0, U_{HX} < 0, U_{XA} = 0$.

In Appendix 1, we derive the first order conditions and the steady state of the model, which yields the equilibrium citizen behavior, X*, reflecting the risk of terrorist attacks and the government's communication of risk to insure normalcy:

$$X^* = X(A(F(G),G)) \qquad (4)$$

We consider content of the government message G as a continuum of information. In the experiment that follows, we consider three levels of G. First, the government provides no information. The next level of G involves the government giving precise information about the risks affiliated with one of two choices the citizen can make. At the highest level of G, the government gives precise information about the risks affiliated with both choices a citizen can make.

Considering Eq. (4) the model yields an increasing response, indicating a greater level of resilience, of the public to government messaging:

$$\frac{dX^*}{dG} = X_A(A(F(G),G))(A_F F_G + A_G) > 0 \qquad (5)$$

In Eq. (5) credible government messaging positively affects normalcy through two channels: In the first channel, captured by the term $X_A A_F F_G$, credible government messaging impacts positively the use of infrastructure by citizens, which increases its efficient use and increases citizen resilience, leading to normal behavior even in the event of a terrorist attack; in the second channel given by the term $X_A A_G$, government messaging focuses on the overall behavior of the citizen in the face of terrorism. According to Eq. (5), if the government has a credible message to communicate and does so through the appropriate communication channels, delivering decision-relevant information, concisely and comprehensibly, the citizen reacts positively and continues to engage in risky behavior. Thus, quality government-supplied information increases the resilience of the public when under threat from potential terrorist attacks.[v]

IV. Experimental Design and Protocol

Experimental approaches are becoming increasingly common in the study of international relations. As McDermott (2011, p. 504) explains, "a key concern (in any study) revolves around the ability of the investigator to isolate and control the variables of interest in order to determine their influence on outcome, and often the laboratory offers a much better environment in which to assert such control (for international relations)". Furthermore, given the difficulty in manipulating resilience and terrorist threat while controlling for extraneous factors (Arce, Croson, and Eckel, 2011), a laboratory environment offers the ideal setting to test how varying the quality of information of low probability negative shocks (proxy for terrorist attacks) influences subjects' decisions on whether to take a risky gamble offering a higher payoff in expectation relative to a safer option that offers a lower payoff for sure. As several scholars argue (Klar et al., 2002; Bar-Tal and Sharvit, 2008), uncertainty about the risk from terrorism and the fear it engenders may have a larger (negative) effect than direct exposure. A laboratory experiment is an ideal method to isolate the effect of information precision on resilience.

The experiment took place in the New York University Center for Experimental Social Science (CESS) laboratory. Subjects were recruited electronically via the CESS laboratory subject pool. 45 subjects participated in one of three sessions of the experiment that lasted approximately 50 minutes each. Subjects were given a show-up fee of $10 and earned a further $9.98 on average over the course of the experiment (depending on their choices) for an average total of $19.98.[vi]

All decisions during the course of the experiment took place via computer and were programmed using the Z-tree software (Fischbacher, 2007). The experiment was decision theoretic—subjects' payments only depended on their own decisions and not those of other subjects. Once they arrived in the lab, they were given a brief set of instructions (see Appendix 2) on the game. The experiment lasted for 75 periods. The number of points earned each period was not cumulative. Instead, subjects earned money from the sum of 10 randomly chosen periods (Morton and Williams, 2010).

Each period, subjects chose from three options: *A, B,* and *C* in which they potentially earned (or lost) points in different amounts that were redeemed at the end of the experiment for cash (25 points=1 dollar). Option *C* was a safe option, and gave them 10 points with certainty. Options *A* and *B* were lotteries that offered subjects some probability ($p \geq .75$) that they would win points and a smaller chance ($p \leq .25$) that they would lose points. However, the expected value of the lotteries of *A* and *B* were identical and equal to 20 points. The decision to make the probability of losing points "rare" mimicked the low probability of a successful terrorist attack. Additionally, the different risks and rewards associated with the lotteries (*A* and *B*) and the safe option (*C*) measured how vague warnings and/or precise information about the probabilities associated with the gambles or adverse shocks (i.e., losing a lottery) may affect subjects' willingness to choose an optimal gamble (20 points in expectation) over a suboptimal sure thing (10 points). One way to conceptualize the differences between options *A, B,* and *C,* is to think of transportation decisions faced by an individual citizen under the threat of a terrorist attack (e.g., an individual living in Jerusalem during the height of the 2nd Intifadah). A citizen can choose to stay home (option *C*) and not expose themselves to the risk from a terrorist attack or choose the riskier, but better, from a societal and individual standpoint, option and take the bus or train (options *A* or *B*) and go to work. Although *A* and *B* have identical expected values, one of the lotteries had a larger potential loss ("higher loss" outcome) than the other ("lower loss" outcome). There were five different lottery combinations that subjects randomly received (see Figure 1).

We recognize that while our experiment is decision-theoretic, it implicitly assumes that a government has perfect and complete information about a terrorist threat. This is a fairly strong assumption, but it is not central to our experiment. The only assumptions needed for our model is (1) the government has better information about the terrorist threat than the citizen and (2) the effect of the level of information on resilience is monotonic (e.g., more information increases resilience).

[Table I here]

The 75 periods were divided into five treatment blocks of 15 periods each. The probabilities from Table I were randomly assigned for each subject to a random block. For each block, subjects were aware of the possible gains and losses associated with each lottery (option *A* and *B*), but the amount of information about their probabilities contained in the warnings varied across blocks. We also issued non-specific warnings about the lotteries in certain treatments. We used losses as opposed to gains when warning the subjects about the lotteries or providing information about the probabilities. Prospect Theory (Kahneman and Tversky, 1979) hypothesizes that individuals are more risk averse in the domain of losses, thereby making this a tougher test of resilience. Focusing on losses also gives the study greater external validity, as government warnings about terrorist attacks are negatively framed. The different information available to subjects from block to block is our experimental treatment. The five treatments are:

1. **No Notification:** Subjects received no message about the underlying probabilities for *A* or *B*. They were only aware of the gains and losses associated with the *A* and *B* lotteries.
2. **Non-Specific Warning One:** Subjects received a warning before each period about *A* or *B*. The warning flashes across the screen in red and says, "Choosing *A* (*B)* may cost you points."
3. **Non-Specific Warning Both:** Subjects received a warning before each period about *A* **and** *B*. The warning flashes across the screen in red and says, "Choosing *A* or *B* may cost you points."
4. **Non-Specific Warning One, Complete Information Other:** Subjects received notifications before each period about *A* **and** *B*. For one option, a non-specific warning flashed across the screen in red and said, "Choosing *A (B)* may cost you points." Subjects also received an additional warning in red that gave them complete information about the underlying probability about one of the choices. This complete information warning stated that "Choosing *B (A)* has [insert probability] of costing you points" (see Figure 1 in Appendix 3).
5. **Complete Information Both:** Subjects received notifications with complete information about *A* **and** *B* before each period. These two warnings flashed in red across the screen and gave the probabilities for the lotteries associated with *A* and *B*. "Choosing *A* has a [insert probability] of costing you points." And "Choosing *B* has a [insert probability] of costing you points."

At the beginning of each period, the subjects' screens were frozen for 5 seconds with the notifications displayed (except for treatment 1, which was frozen with no notification). After 5 seconds, the subjects were given up to 20 seconds to make their choice between *A*, *B*, and *C*.[vii] When transitioning between treatments, the subjects received a screen alerting them that the payoffs to choices *A* and *B* and their probabilities had changed. The order in which subjects received the treatment blocks was randomized along with the pairs of probabilities from Figure 1 that were assigned to each treatment block. Whether the higher loss option or the lower loss option appeared on top as choice A was also randomly varied from block to block.

V. Data and Results

Across all treatments, over 82% of the time subjects chose the risky options (*A* or *B*). Table II summarizes how subjects divided their choices among the safe option, the lower loss, and the higher loss options by treatment.

[Table II here]

When choosing a lottery, most subjects avoided the option with the potential for higher losses. The lower loss option was more frequently chosen than the higher loss option across all treatments. Beginning with the *No Notification* treatment, subjects chose the *safe option* at a rate of 22.4%, the *lower loss option* at 62.1%, and *the higher loss option* at 15.6%. Comparing this to the *Complete Information Both* treatment, subjects chose the *safe option* 12% of the time, *the lower loss option* 54.9% of the time, and the *higher loss option* 33.1% of the time. Thus, adding complete information nearly halves the number of times subjects chose the suboptimal *safe option*, shifting subjects towards the riskier choices with higher payoffs in expectation. Furthermore, complete information made subjects more willing to accept the *higher loss option* once they knew the lower probability of losing associated with it (relative to the *lower loss option*), but they still preferred the *lower loss option*.[viii]

Meanwhile, *Non-Specific Warnings*, which gave no additional information to the subject, had little effect on the subjects' willingness to take a risky choice. The *Non-Specific Warning Both* treatment actually decreased subjects' selection of the *safe choice* by about 2% while having little effect on choosing the *higher loss option* relative to the *lower loss option*. Where these warnings had an effect was in shifting choices between the *higher loss option* relative to the *lower loss option* in the *Non-Specific Warning One* treatment. A single warning about the *lower* *loss option* resulted in about a 10% decrease in the selection of that choice relative to the *No Notification* treatment. A single warning about the *higher loss option* resulted in a similar decrease.

Next, we address how the various treatments influence subjects decisions on whether to choose a risky option or not (e.g., how do they change the binary variable *risky choice*) or the increasing risk in choice decisions (i.e., the variable *choice*, which ranges from the *safe option* =0 to the *higher loss* option=2).[ix] Table III below includes dummy variables for all the treatment effects relative to the *No Notification* treatment.

[Table III here]

From Table III (Models 1-3) it appears that providing more information relative to *No Notification* treatment increases subjects' willingness to choose the lottery options (*A* or *B*) and take on greater amounts of risk. Only *Non-Specific Warning Both* had no effect on subjects compared to the *No Notification* treatment, which is unsurprising given that this treatment gave subjects no new information. In treatment blocks where subjects were given complete information, they were the most willing to take risks and choose the lottery options (the magnitude and sign on *Complete Both*). This, again, is not surprising since the lottery options are relatively safe and promise a higher expected payoff than the *safe option*. However, despite no additional information, *Non-Specific Warning One* does have an effect. As seen in Table II and Table VI Model I from the appendix, this effect results from vague warnings about *the lower loss option*, which scares subjects off that option towards the higher loss options but not towards the safe option.

Table III also examines the panel structure of the data, adding fixed effects, time trends—including dummy variables for blocks[x] (*Time Trends*) and then within block dummies[xi] (*Within Treatment Block Trends*) and their lagged choice (*Lag Choice)* and whether they lost in the previous period (*Lag Loss Previous Period*) to further examine how the treatments and dynamics of the experiment influenced subjects' choices. Model 4 shows that the results from Models 1-3 with respect to treatment effects largely hold. All the treatments with the exception of the *Non-Specific Warning Both* increase subjects' willingness to select the lotteries (*Risky Choice*) relative to the no-information treatment. Additionally, subjects who chose a lottery option in the previous period were also likely to choose a lottery in the following period (the positive and significant coefficient on *Lag Choice*). However, losing in a previous period did not influence subjects' decision on whether to choose the lottery or not.

For Models 3 and 5, we use a Tobit model to account for the right and left-censored nature of the dependent variable (*Choice)*.[xii] The results suggest that the effect of subjects' willingness to choose potential "riskier" choices is similarly positively influenced by all the treatments (except *Non-Specific Warning Both*) relative to the baseline, no information treatment. Moreover, losing in the previous period (the binary variable *Lag Loss Previous Period*), makes subjects less-willing to choose more risky choices in the subsequent period.

Given these results, it may be helpful to look at how subjects' choices change over time. We construct a variable *Change Choice*, which measures how a subject changes the variable *Choice* from the previous period to the current period. Table IV presents a summary of the variable *Change Choice.*

[Table IV here]

Most subjects stuck to the choice they had made in the previous period. Moreover, the symmetric nature of the above distributions suggests that subjects were not necessarily increasing to risky decisions or decreasing to less risky decisions—but equally likely to make either change. Table V examines the effect of the treatments and dynamic aspects on subjects' willingness to change choices.

[Table V here]

Table V, Model 1 largely confirms the results in Table 5. All of the treatments, with the exception of the *Non-Specific Warning Both*, increase subjects' willingness to change to risky options relative to the no information case. Moreover, in the face of previous losses, subjects are less likely to change their choices to more risky options.

To further examine how the treatments influence subjects' decisions to change their choices, we divide the data based on what they chose in the previous period. Model 2 looks at what happens when subjects chose the safe option in the previous period (*Choice*=0). For subjects choosing the safe option, only the complete information treatment has an effect (a positive one) on increasing their willingness to take on risk in the next round. Model 3 examines subjects who chose the lower potential loss lottery in the previous period (*Choice*=1). As in Model 2, only the complete information treatment has any effect—it increase subject's willingness to choose higher levels of risk relative to the no-information treatment (move from the lower potential loss to the higher potential loss). Interestingly, it does not seem that a loss in the previous period induces subjects to choose the less risky option (i.e., move from the lower potential loss to the safe option). Model 4 examines subjects who chose the higher potential loss (*Choice*=2) in the previous period. In contrast to the dynamics in Models 2 and 3, all treatments with the exception of the complete information *increase* subjects' willingness to take risk relative to the baseline case.[xiii] Moreover, previous losses seem to decrease subjects' willingness to choose the higher loss option (the positive and significant coefficient on *Lag Previous Loss*). This result, along with the insignificant sign on *Lag Previous Loss,* suggests that previous losses have little effect on choosing between a safe and a risky option, but seems to increase the likelihood of moving from the higher loss to lower loss option. Subjects do not stop playing the lottery after a loss, but rather make what they perceive to be a safer choice.

The results from the experiment are interesting and somewhat counterintuitive. In general, additional *concrete* (not vague) information about risks increases subjects' willingness to choose the optimal risky option (choices *A* and *B*) relative to the lower, safer payoff (*C*). Subjects who previously chose the safe option or the less risky option only take on more risk in the next round when they have complete information (Table V, Models 2 and 3). However, the opposite is true of subjects who are already choosing the most risky option (Table V, Model 4). In addition, the effect of losing in the previous period is to shift away from a more risky lottery to the safer lottery.

Furthermore the results in Table II and Table VI in the Appendix suggest that a significant amount of variance in subjects' behavior is due to warnings that contain no additional information (*Non-Specific Warnings*). The second and third rows in Table 2 highlight this point. In the *Non-Specific Warning (higher loss)* subjects choose the safe option approximately 70% of the time and the higher loss gamble one-sixth as much, compared to the *Non-Specific Warning (lower loss*). The vague warnings, then, shift subjects' choices between lotteries, but do not affect how likely they are to select the safe choice over one of the lotteries. These findings echo Fox and Tversky (1995) and reveal that vague warnings may influence subjects to make less than optimal decisions. Although our two lotteries have equal expected values, the drastic effect of receiving a warning about one of the lotteries suggests that a warning about a lottery with a higher expected value may alarm subjects enough to choose a lottery with a lower expected value. Therefore, policymakers should be circumspect when making vague statements about threats given its effect on risk-taking behavior.

VI. Conclusion

This paper has examined the effect of warnings on resiliency during an ongoing terrorist threat. We defined resiliency as the continued willingness to take risks despite knowledge of potential adverse outcomes such as a successful terrorist attack. The theoretical model follows Fischhoff (2006) and predicts that the more information the government provides about potential threats, the more resilient the citizenry should be. Well-informed citizens should be more willing to make optimal, though somewhat risky, choices as the government increases the precision of its warning messages.

We then ran a laboratory experiment to test the predictions of the model. Overall, the results of the experiment suggest that precise warnings about the threat of a terrorist attack can contribute to increasing resiliency among citizens. In an uncertain environment, good warnings with actionable information allow citizens to weigh the probability of potential losses associated with a successful terrorist attack more carefully and continue with the activities of daily life when compared with no warning messages. However, in situations where citizens are aware of potential terrorism but the probability is low, warning messages without specific information may adversely affect citizens' choices. Messages with no specific information do not allow citizens to evaluate risk appropriately, making them no better them no warning message at all and potentially leading to suboptimal outcomes for the individual and society.

The results of the experiment did not show a simple relationship between resiliency and warning messages. While complete information about the nature of the risk increased subjects' willingness to make risky choices, non-specific warnings may have been worse than the absence of any information or warning. Furthermore, subjects who demonstrated a reluctance to take risks only increased their willingness to do so later when given full information about the uncertainty associated with each lottery.

The policy implications of this paper are clear. We agree with Shapiro and Seigal (2010) when they argue that governmental sharing of counter-terror information benefits society. In situations where citizens already know they are living under threat from terrorism, governments seeking to alert their citizens to specific threats without causing panic should give as precise information as possible. General reminders about the possibility of attack appear to make citizens overly risk-adverse, needlessly deterring them from engaging in the low-risk daily activities.

Appendix 1: Theoretical Model First Order Conditions and Steady State

The corresponding Hamiltonian for the citizen's problem is:

$$L = U(X,H,A) + \lambda_1 a(X-H) + \lambda_2 f(A,F,G) + \lambda_3 g(A,F,G) \quad \text{(A.1)}$$

Where $\lambda_1, \lambda_2\ \lambda_3$ are, respectively, the shadow prices of habits, infra-structure and terror attacks. The first order conditions are:

$$U_X + \lambda_1 a = 0 \quad \text{(A.2)}$$

$$\dot{\lambda}_1 - r\lambda_1 = -U_H + a\lambda_1 \quad \text{(A.3)}$$

$$\dot{\lambda}_2 - r\lambda_2 = -\lambda_2 f_F - \lambda_3 g_F \quad \text{(A.4)}$$

$$\dot{\lambda}_3 - r\lambda_3 = -U_A - \lambda_2 f_A - \lambda_3 g_A \quad \text{(A.5)}$$

Deriving (A.2) with respect to time and using (A.3) yields

$$\dot{X} = \frac{U_X}{U_{XX}}(r+a) - \frac{U_{XH}}{U_{XX}}a(X-H) + \frac{aU_H}{U_{XX}} \quad \text{(A.6)}$$

Noticing that $\dot{X}$ is a function of *A*, and *H* we can rewrite Eq. (A.6) as:

$$\dot{X} = X(H,A) \quad \text{(A.7)}$$

Solving the model in the steady state yields:

$$\dot{H} = 0 \Rightarrow X = H \quad \text{(A.8)}$$

$$\dot{X} = 0 \Rightarrow X(H,A) = 0, f\,rom (A.8) \Rightarrow X = X(A), X_A > 0 \quad \text{(A.9)}$$

$$\dot{F} = 0 \Rightarrow f(A,F,G) = 0 \quad \text{(A.10)}$$

$$\dot{A} = 0 \Rightarrow g(A,F,G) = 0 \quad \text{(A.11)}$$

It follows from Eqs. (A.10) and (A.11) that:

$$A = A(F(G), G), A_F > 0, A_G > 0, F_G > 0 \quad (A.12)$$

Substituting (A.12) into (A.9) yields the equilibrium citizen behavior reflecting the risk of terrorist attacks and the government effort of communicating the risk to insure normalcy:

$$X = X(A(F(G), G)) \quad (A.13)$$

Appendix 2: Lab Instructions

Thank you for your attendance in the CESS lab for our experiment. During the experiment you will make decisions. If you make your decisions carefully you can walk out of here with more money. Everyone will be given a show-up fee of $10.00. For the experiment you will not be partnered with anyone else, nor will your payoffs depend upon what anyone else does. They will only be the result of YOUR OWN DECISIONS. Throughout the experiment you will earn points that can be redeemed at the end of the experiment for cash in addition to your show-up fee of $10. 25 points=1 dollar

The experiment will last for 5 blocks. In each block, there will be 15 rounds for a total of 75 rounds in the experiment. In each round you will choose between three options labeled "A", "B", and "C". When you initially click into a round, you will have 5 seconds to scan the screen and the choices. During this 5-second period you cannot make a choice. After 5 seconds, you can then choose between A, B, and C. There is a counter in the upper right corner of your screen. If you do not chose an option, A, B, C in the 20 second allotted time you will receive a payoff of zero for the round. Two of the options are lotteries in which there is some probability (p) that you can win points and some probability (1-p) that you can lose points. The other option will guarantee that you win ten points. You will always know how many points you can earn or lose with the lotteries --this will be displayed in the lower left hand corner of the screen—however your information about the probabilities will vary.

Your payoff will be the sum of points from 10 randomly chosen rounds plus the show-up fee of 10 dollars. Furthermore, you will earn an additional 50 points by filling out the survey we are passing out. This important: if the sum of the 10 randomly chosen rounds plus the 50 points for the survey is negative, you will still be awarded to the full show-up fee, but that is all. If you have any questions, do not hesitate to ask one of us.

Appendix 3: Screen Shot of the Game

[Figure I here]

Appendix 4: Breaking out the Non-Specific Warning

[Table VI here]

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Tables and Figures

Higher Loss				Lower Loss				
Prob. Win	*Value Win*	*Prob. Lose*	*Value Lose*	*Prob. Win*	*Value Win*	*Prob. Lose*	*Value Lose*	*Expected Value*
0.975	25 pts	0.025	-175 pts	0.850	50 pts	0.150	-150 pts	20 pts
0.950	30	0.050	-170 pts	0.825	55 pts	0.175	-145 pts	20 pts
0.925	35 pts	0.075	-165 pts	0.800	60 pts	0.200	-140 pts	20 pts
0.900	40 pts	0.100	-160 pts	0.775	65 pts	0.225	-135 pts	20 pts
0.875	45 pts	0.125	-155 pts	0.750	70 pts	0.250	-130 pts	20 pts

Table I: Lotteries for Options

	Safe Choice Raw Freq.	**Safe Choice %**	**Lower Loss Raw Freq.**	**Lower Loss %**	**Higher Loss Raw Freq.**	**Higher Loss %**
No Notification (675 obs.)	151	22.37%	419	62.07%	105	15.56%
Non-Specific Warning (lower loss) (330 obs.)	40	12.12%	174	52.73	116	35.15%
Non-Specific Warning (higher loss) (345 obs.)	71	20.58%	252	73.04%	22	6.38%
Non-Specific Warning (both) (675 obs.)	136	20.15%	432	64.00%	107	15.85%
Complete Info. Low, Non-Specific Warning High (375 obs.)	71	18.93%	260	69.33%	44	11.73%
Complete Info. High, Non-Specific Warning Low (296 obs.)	36	12.16%	165	55.74%	95	32.09%
Complete Info. Both (674 obs.)	81	12.02%	370	54.90%	223	33.09%
Total(3,370 obs) xiv	586	17.39%	2,072	61.48%	712	21.13%

Table II: Summary of Distribution of Subject's Choices by Treatment

	Model 1	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Method	Linear Probability Model	Logit	Tobit	Logit Panel by Period	Tobit Panel by Period
Dep. Variable	*Risky Choice (0,1)*	*Risky Choice (0,1)*	*Choice (0,1,2)*	*Risky Choice (0,1)*	*Choice (0,1,2)*
Constant	0.776*** (0.043)	1.244*** (0.245)	0.852*** (0.085)		
Non-Specific Warning One	0.059** (0.029)	0.381** (0.187)	0.133* (0.072)	0.524*** (0.195)	0.112** (0.045)
Non-Specific Warning Both	0.022 (0.024)	0.133 (0.147)	0.034 (0.062)	-0.074 (0.190)	0.002 (0.045)
Non-Specific Warning One, Compl. Info. One	0.059* (0.033)	0.381* (0.214)	0.143* (0.079)	0.436** (0.193)	0.102** (0.047)
Complete Both	0.102*** (0.029)	0.734*** (0.199)	0.322*** (0.074)	1.036*** (0.215)	0.292*** (0.047)
Lag Choice				0.763*** (0.142)	0.488*** (0.061)
Lag Loss Previous Period				0.180 (0.215)	-0.077* (0.039)
Fixed Effects	No	No	No	Yes	Yes
Time Trends	No	No	No	Yes	Yes
Within Treatment	No	No	No	Yes	Yes
Block Trends					
N[xv]	3375	3375	3370	2380	3145

*p<0.10 *, p<0.05 **, p<0.01 ****

Table III: Treatment Effects (note robust standard errors clustered on each subject in parentheses)

Change Choice	**Raw Frequency (out of 3,145 obs.)**[xvi]	**Percentage**
-2	55	1.75%
-1	354	11.26%
0	2,318	73.70%
1	357	11.35%
2	61	1.94%

Table IV: Summary of Change Choice

	Model 1	Model 2	Model 3	Model 4
Method	Tobit Panel by Period	Tobit Panel by Period	Tobit Panel by Period	Tobit Panel by Period
Dep. Variable	*Change Choice (-2,-1,0,1,2)*	Change Choice (0,1,2) if *Lag Choice=0*	Change Choice (-1,0,1) if *Lag Choice=1*	Change Choice (-2,-1,0) if *Lag Choice=2*
Non-Specific Warning One	0.070** (0.029)	0.070 (0.249)	-0.001 (0.035)	0.909*** (0.256)
Non-Specific Warning Both	-0.005 (0.029)	-0.111 (0.253)	-0.007 (0.035)	0.781*** (0.283)
Non-Specific Warning One, Compl. One	0.068** (0.029)	0.099 (0.259)	0.018 (0.034)	0.583** (0.261)
Complete Both	0.183*** (0.030)	1.368*** (0.271)	0.173*** (0.037)	0.267 (0.225)
Lag Choice	-0.729*** (0.175)			
Lag Loss Previous Period	-0.052** (0.026)		-0.015 (0.026)	-0.746*** (0.260)
Fixed Effects	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes
Within Treatment Block Trends	Yes	Yes	Yes	Yes
N	3145	547	1928	670

*p<0.10 *, p<0.05 **, p<0.01 ****

Table V: Changing Choices (note robust standard errors clustered on each subject in parentheses

	Model 1	Model 2	Model 3	Model 4	Model 5
Method	Tobit Panel by Period	Tobit Panel by Period	Tobit Panel by Period	Tobit Panel by Period	Tobit Panel by Period
Dep. Variable	*Choice (0,1,2)*	*Change Choice (-2,-1,0,1,2)*	Change Choice (0,1,2) if *Lag Choice=0*	Change Choice (-1,0,1) if *Lag Choice=1*	Change Choice (-2,-1,0) if *Lag Choice=2*
Non-Specific Warning High	-0.067 (0.055)	-0.051 (0.036)	-0.341 (0.278)	-0.069* (0.042)	0.674* (0.410)
Non-Specific Warning Low	0.320*** (0.059)	0.198*** (0.037)	1.010*** (0.399)	0.091** (0.047)	1.000*** (0.286)
Non-Specific Warning Both	0.000 (0.045)	-0.006 (0.029)	-0.071 (0.251)	-0.006 (0.034)	0.780*** (0.284)
Compl. Info. High, Non-Specific Warning Low	0.230*** (0.060)	0.156*** (0.038)	-0.184 (0.391)	0.074 (0.048)	0.505 (0.310)
Compl. Info. Low, Non-Specific Warning High	0.005 (0.054)	0.002 (0.035)	0.333 (0.309)	-0.020 (0.040)	0.684* (0.360)
Complete Both	0.293*** (0.046)	0.186*** (0.029)	1.38*** (0.268)	0.174*** (0.037)	0.270 (0.225)
Lag Choice	0.465*** (0.028)	-0.7458*** (0.018)			
Lag Loss Previous Period	-0.080** (0.039)	-0.053** (0.026)		0.010 (0.026)	-0.742*** (0.260)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Trends	Yes	Yes	Yes	Yes	Yes
Within Treatment Block Trends	Yes	Yes	Yes	Yes	Yes
N	3145	3145	547	1928	670

*p<0.10 *, p<0.05 **, p<0.01 ****

Table VI: Results with whether the higher loss or lower loss outcome received the vague warning. Model 1 reproduces Model 5 from Table III. Models 2-5 reproduce Models 1-4 from Table V (note robust standard errors clustered on each subject in parentheses)

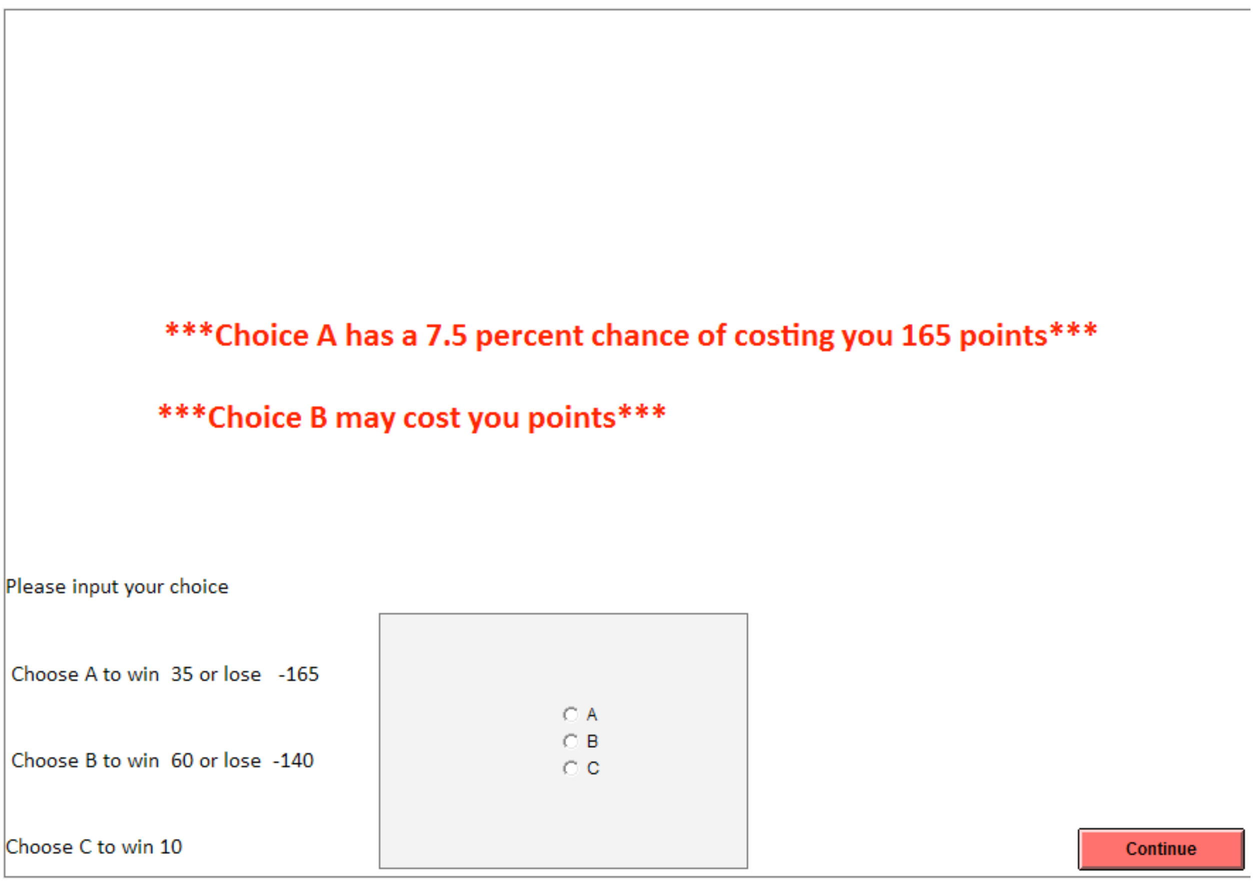

Figure I: Screen Shot of Vague Warning One, Complete Information Other Treatment

Endnotes

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[i] See remarks by Secretary of Homeland Security Janet Napolitano http://www.dhs.gov/ynews/speeches/sp_1284133372649.shtm

[ii] See ABC News "DHS to Scrap Color Code Terror Alerts by April."

[iii] For instance, Fischhoff and his co-authors have shown that when it comes to assessments of low-probability, high-consequence events, citizens are most skeptical of claims for which experts' evidence is weakest (e.g., Fischhoff et al., 1981, Fischhoff et al., 1983, and Fischhoff et al., 2002)

[iv] See Faria and Silva (2011) for a model where Habit formation characterizes the behavior of the terrorist organization: at any period, terrorists derive complementary utility from past and contemporaneous levels of successful attacks.

[v] According to Eq. (5) we have two distinct effects from government messaging (infrastructure and behavior of citizen in face of attack) and both are most likely positive. In order to have to resilience weakly increasing in government messaging, one effect would have to have the opposite signs, which is not the case, or both would be equal to zero, which is also unlikely.

[vi] It was possible for students to end up with less than $10 in earnings if the lost money the playing the game. When this occurred, they were just given the show up fee of $10.

[vii][vii] If the subjects failed to enter a choice before the end of the 20 second time limit, they were awarded 0 points. This occurred only 5 times in 3375 rounds.

[viii] We thank an anonymous reviewer for suggesting this formulation of the results.

[ix] We interpret the higher loss option as a "more risky" choice. Even though lotteries A and B have equal expected values, given the lack of information subjects had in some treatment blocks, and the way they actually behaved, it is logical to order the riskiness of the choices as going from safe, lower loss, higher loss.

[x] For instance, periods 1-15, 16-30, etc.

[xi] Each block was further subdivided into 3 five-period blocks, so the first five periods, second five periods, and the final five periods of a block received dummies.

[xii] One way to interpret this censored nature, is that it is plausible in alternative setting that some subjects would be willing to choose an even safer option than safe option (e.g. their *Choice*<0) or a more risky option than the riskiest lottery (i.e. their *Choice*>2). The Tobit model takes this into account.

[xiii] Given the censored nature of the dependent variable, one can say that hypothetically, subjects would want to take a higher risk option than *Choice*=2 if it were available.

[xiv] 5 observations were dropped due to subject not deciding in the time allotted to them and thus classified as a non-risky choice.

[xv] Some of the observations were dropped due to a lack of variation. Also due to the inclusion of the lagged variables—which we did not lag across treatment blocks—some further observations were lost.

[xvi] The reduced number of observations is due the fact that we cannot lag across treatment blocks because the probability and payoffs associated with the choices changed.