Risk Analysis, Vol. 32, No. 4, 2012 DOI: 10.1111/j.1539-6924.2011.01733.x

Risk Perception and the Economic Crisis: A Longitudinal Study of the Trajectory of Perceived Risk

William J. Burns[1,2,*] Ellen Peters,[3] and Paul Slovic[1,4]

We conducted a longitudinal survey of public response to the economic crisis to understand the trajectory of risk perception amidst an ongoing crisis. A nation-wide panel responded to seven surveys beginning in late September 2008 at the peak of the crisis and concluded in October 2009. At least 600 respondents participated in each survey, with 413 completing all seven surveys. Our online survey focused on perceptions of risk (savings, investments, retirement, job), negative emotions toward the financial crisis (sadness, anxiety, fear, anger, worry, stress), confidence in national leaders to manage the crisis (President Obama, Congress, Treasury Secretary, business leaders), and belief in one's ability to realize personal objectives despite the crisis. We employed latent growth curve modeling to analyze change in risk perception throughout the crisis. Our results suggest that, in general, people's perceptions of risk appear to decrease most rapidly during the initial phase of a crisis and then begin to level off. Negative emotion about the crisis was the most predictive of increased risk perception, supporting the notion of risk as feelings. Belief in one's ability to realize personal objectives was also predictive. Confidence in national leaders, however, was not predictive of perceived risk. Finally, our results demonstrate that groups may experience a crisis differently depending on a combination of personal characteristics such as gender, income, numeracy, and political attitude. Risk management and communication should work in sync with these mechanisms and differences across groups.

KEY WORDS: Confidence; emotion; hedonic adaptation; latent growth curve; risk perception

1. INTRODUCTION

1.1. The Dynamics of Perceived Risk

Prominent events, through their scope and salience, have the ability to shape our feelings, perceptions of risk, and a wide range of risk-related behaviors. Certainly, the past decade has witnessed many influential events within the United States that have reverberated around the world. Notable examples are the collapse of the dot-com bubble (2000), the Supreme Court decision in the 2000 presidential election, the September 11 terrorist attacks on New York and Washington (2001), the war in Iraq (2003), the escalation of returns in the housing and security markets (2000–2007), and the near collapse of the U.S. economy (2008–2009). Public reaction to these and similar events have had profound and long-lasting societal impacts.

Accordingly, public response to natural, technological, and political/military hazards has been studied for decades.[(1)] Often, hypothetical scenarios or vignettes based on past mishaps have been used to investigate which factors contribute to heightened perceptions of risk and reactions resulting from

[1]Decision Research, Eugene, OR, USA.
[2]Information Systems and Operation Management, Cal State University, San Marcos, CA, USA.
[3]Department of Psychology, The Ohio State University, OH, USA.
[4]University of Oregon, OR, USA.
*Address correspondence to William J. Burns, Decision Research, 1201 Oak St., Eugene, OR 97401, USA; tel: 541-485-2400; fax: 541-485-2403; bburns@csusm.edu

0272-4332/12/0100-0659$22.00/1 © 2011 Society for Risk Analysis

those perceptions.[2] One of the most robust findings emerging from this research suggests that threat events that are construed as uncertain and uncontrollable, and dreadful to contemplate, heighten perceived risk. These construals are often influenced by a number of factors, including personal characteristics (e.g., gender, numeracy, political or cultural views), confidence in those managing the risk (e.g., first responders, local officials), and belief in one's ability to cope with the adverse event.[3–5]

What is not understood is how perceived risk toward a threatening circumstance changes over time. It is also not clear how factors such as negative emotion or confidence in managerial competence correlate with perceived risk throughout and after a disaster. To address these issues, this article investigates the trajectory of perceived risk during the economic crisis from September 2008 to October 2009. This severe economic downturn provides a unique opportunity to study perceived risk and its related factors because it is an ongoing crisis that has significantly affected people from all strata of American society.[6] Specifically, we examine how perceived risk with regard to factors such as employment or retirement changed in response to changes in negative emotion, confidence in the nation's leaders to manage the financial crisis, and belief in one's own ability to cope with the crisis. Our study began as the stock market experienced its worst week in history and extraordinary emergency measures were taken by Congress to rescue the U.S. and global economies. What follows next is a discussion of two feedback mechanisms that we believe influence the trajectory of public response during a crisis. After that, we discuss the expected relationships between perceived risk and its key correlates.

To understand the trajectory of public concern regarding the financial crisis, we begin with the observation that crises typically involve two phases, each with their own dynamics. First, perceived risk and negative emotions often escalate in the beginning of a crisis as the public responds to news reports, social media, and conversations with friends and family.[7] Second, these heightened perceptions and emotions also decrease at some point as steps are taken to address the problem and people have time to adjust.[1,8,9] The escalation of public reaction can be characterized by a reinforcing feedback loop consisting of media coverage, negative emotions, perceived risk, and risk-related behaviors. For example, as media coverage of a crisis increases, negative emotions and perceived risk are likely to increase, which in turn may increase risk-related behaviors, which then invite more media coverage, and so forth. The amplifying mechanisms and subsequent ripple effects connected with this process have been reported by several researchers.[10–12]

However, the unbounded escalation of negative emotions like fear or anger is neither desirable for an individual or a society nor in most circumstances sustainable, and will eventually be brought under control by balancing feedback loops consisting of individual, community, and even nation-wide factors. For example, as fear and perceived risk begin to rise in a community, officials may offer support and reassurance that the crisis is being addressed.[13] The effectiveness of this reassurance will be mitigated by the level of confidence in those managing the crisis.[14,15] Individuals may also adjust to the crisis by helping others or realigning their expectations in accord with current challenges. Personal coping skills and resources will play an influential role in this adjustment.[16] These efforts will in time drive perceived risk and negative emotions toward more normal levels. How soon this happens depends on a variety of factors, including the type of disaster, how effectively the crisis is handled, and individual characteristics. The rise and decline of perceived risk during a crisis is complex and subject to a variety of factors. However, the interaction of these two feedback loops provides a helpful window from which to observe the trajectory of perceived risk as the crisis unfolds.

Regarding the escalation of public concern, it may be hard to know when people began to worry seriously about the economy. Certainly by late September 2008, anxiety was high amidst the near collapse of major financial institutions and the massive selloffs in the financial markets. Media coverage was extensive and often sensationalistic, using phrases like "economic meltdown" and drawing comparisons to the Great Depression. In desperation, a rescue bill and later a stimulus package were passed that would prove to be extraordinarily divisive politically. It would seem, with so much uncertainty and potential for calamity, the public would remain paralyzed with anxiety and heightened perceptions of risk. Yet we know, in retrospect, that is not what happened. This article explores how risk perceptions changed; it also examines those factors potentially responsible for keeping these perceptions and emotions in check. Those factors that might have facilitated a return to precrisis levels of perceived risk and negative emotions are discussed next.

Emotional reactions to a stimulus or an event frequently subside (or increase) to a baseline through a process known generally as hedonic adaptation.[17] During times of crisis such adaptation can serve to protect a person from prolonged fear and stress that, unchecked, can become debilitating. According to Frederick and Lowenstein, adaptation may be physiological, perceptual, or behavioral. Solomon[18,19] researched the physiological aspect of this phenomenon and contended that if something causes an individual to feel more negative, a bodily process (an opponent process) will work to bring that negative reaction back to the person's baseline emotional level. He further postulated that this opponent process is strengthened with use. That is, emotional responses are dampened more effectively with repeated exposure to an adverse stimulus. He reported that this phenomenon had been observed in the laboratory as well as the field. In line with Solomon's findings, we might expect that, as negative emotions about the financial crisis began to climb to uncomfortable heights, physiological processes should drive these emotions to more moderate levels. Additionally, we might expect that people's emotional response to unpleasant economic news would become less volatile as the crisis continued.

Carver and Scheier[16] have described emotional adaptation as part of a self-regulatory system. As an illustration, they indicate that stress often arises from appraisals that one cannot obtain an important goal. These appraisals evoke negative emotions, and adaptive mechanisms facilitate a return to a less stressful state.[5] This adaptation may involve behavioral strategies to obtain a goal by other means, or it may require altering one's perceptions or expectations. The authors speculate that evolutionary pressures would favor those with the ability to appropriately respond to stressors in the environment. Too little emotional responsiveness might render a person slow to avoid danger. Too much emotional responsiveness might make a person unstable and therefore hinder the ability to cope with danger. A number of researchers have adopted this perspective and have investigated people's ability to regulate emotions like fear, anger, and sadness.[21–23] Similar to Solomon,[18] they have noted that heightened emotions tend to oscillate about a personal baseline and dampen over time. Similarly, people differ in their emotional reactivity, and their ability to regulate these fluctuations. Consistent with these findings, we might expect that, as the magnitude of the financial crisis became apparent, people would engage in different adaptive strategies. For example, many people might shift their interests to less expensive pursuits to accommodate potential shortfalls in their income or investments. This new norm or adaptation level regarding consumption goals would in effect decrease negative emotions by reducing the gap between current and desired levels of consumption. Based on this reasoning, we examine in the present article whether people do differ in their ability to make these shifts, and so thereby vary in the rate with which these emotions' decline would vary.

Central then to our investigation is how negative emotion is associated with perceived risk over time. Research has shown a positive correlation between fear and perceived risk, but anger, which is sometimes a negative emotion, has been found to correlate negatively with perceived risk.[24] As a result, we track a wide range of negative emotions to observe their relationship to perceived risk. With the possible exception of anger, our contention was that as negative emotional reactions to the financial crisis subside, so should perceived risk.

Also important are people's expectations about their ability to realize important objectives amidst the crisis. Carver and Scheier[16] suggest that perceptions of others' capabilities to help, as well as people's assessment of their own ability to prevail, contribute to an expectation of success or failure. Confidence in the management of a crisis should reduce uncertainty and provide a greater sense that the disaster is under control.[25,26] This confidence should be associated with less perceived risk. Belief in one's ability to cope or adjust to the crisis is also important and should be similarly associated with less perceived risk.

We are also interested in how individuals' perceptions of risk might differ at the start of a crisis and how their trajectories of change might differ as the crisis unfolds. Of particular interest is the moderating role of gender and numeracy. A number of studies have shown that women have higher perceptions of risk than men.[27] It is not known whether women's perceived risk declines at the same rate as men's following a crisis. Similarly, more numerate people have been shown to have less perceived risk but it is not known whether they return to baseline levels at the same pace as less numerate people.[28]

We begin with a discussion of pivotal events to provide context for our data collection and analysis. This is followed by a description of our longitudinal

[5]This phenomenon is not universal. For some people, negative emotions may lead to heightened sensitization and still higher levels of negative emotion.[20]

design and a brief introduction to the growth curve modeling central to this analysis. Graphs depict the trajectory of perceived risk and negative emotion, and portray how these may differ by gender and numeracy. Data tables explore how change in perceived risk is related to the election of Barack Obama. The trajectory for perceived risk and its relationship with important covariates are then estimated via a latent growth curve model. We conclude with a discussion of our findings and implications for further research.

1.2. Events Prior to Our Study

To provide a context for our longitudinal study and to appreciate what led to the dramatic rise of public concern in late 2008, we begin by indexing the pivotal events of that year. We follow later with a discussion of events in 2009. Events during the first half of 2008 began to suggest the economy was in trouble. For example, in January 2008 the National Association of Realtors announced that housing sales during the previous year had experienced the largest drop in 25 years. By March, the Dow had fallen by 20% from its previous high five months earlier and Bear Sterns was acquired by JPMorgan Chase to avoid bankruptcy; by June, ex-Bear Stearns fund managers were arrested by the Federal Bureau of Investigation (FBI) for their possibly fraudulent role in the subprime mortgage collapse. However, even with these misfortunes, terms like economic meltdown and comparisons to the Great Depression were not prominent in the news.

Beginning in early September, however, events occurred in rapid succession that put the economy on everyone's radar.[29] Most notably, Fannie Mae and Freddie Mac were taken over by the federal government (September 7), Merrill Lynch was sold to Bank of America, Lehman Brothers filed for bankruptcy (September 15), and the Federal Reserve lent American International Group (AIG) $85 billion to avoid bankruptcy (September 17). Treasury Secretary Henry Paulson and Fed Chairman Ben Bernanke met with key legislators to propose a $700 billion emergency bailout through the purchase of toxic assets; they emphasized the U.S. and world economy may be at stake (September 18). The FBI announced that it was investigating Fannie Mae, Freddie Mac, Lehman Brothers, and AIG for possible fraud (September 23). Washington Mutual became the largest commercial bank ever to fail and was seized by the Federal Deposit Insurance Corporation (September 25).

1.3. Events During Our Study

We launched our first online-panel survey on September 29, 2008. On the same day, the Emergency Economic Stabilization Act was defeated in the U.S. House of Representatives and the Dow fell 778 points, experiencing its largest-ever one-day point drop. Attention to the crisis continued to escalate and on October 3 President Bush signed the Emergency Economic Stabilization Act, creating a $700 billion Troubled Assets Relief Program (TARP) to purchase failing bank assets. During the week of October 6–11, Wall Street experienced its worst week ever and its highest one-day volatility. *During that week we launched our second survey.* On October 13, Treasury Secretary Henry Paulson and Federal Reserve Chairman Ben Bernanke met with the CEOs of the nation's nine largest banks and announced our banking system was in crisis. They proposed to infuse $125 billion into the financial system. This signaled a profound policy shift from protecting against *moral hazard* (letting Lehman Brothers collapse) to protecting against *systemic risk* (some institutions are too big to fail). Early November brought welcome news for many Americans as Barack Obama, campaigning on a theme of hope and change, became the first African-American president. *We distributed our third survey during election week.* On November 24, the U.S. government agreed to rescue Citigroup by infusing the bank with $45 billion. The National Bureau of Economic Research announced on December 1 that the U.S. economy had entered a recession in December 2007. On the same day, the Dow dropped 679 points. *At the close of that week we administered our fourth survey.* Capping off the year, Bernard Madoff was arrested on December 11 by the FBI for perpetrating the largest Ponzi scheme in history.

The year 2009 proved to be less dramatic than 2008, but crises continued. Barack Obama became president on January 20, 2009 and signed the $787 billion stimulus package on February 17. By March 9, the Dow had declined to 6,440, a level last seen in 1996 and representing more than a 50% drop from its October 2007 peak. On March 10, stocks began to rally. *Less than two weeks later we distributed our fifth survey*. By May 6, the Dow had climbed to 8,500, up 33% from its low in March. General Motors filed for bankruptcy on June 1. *In late June and early October, amidst continued concerns about unemployment, we launched our sixth and seventh surveys.*

We surveyed individuals at the specific time periods above (and our results therefore could have been strongly driven by associated events). Gallup polling[30] that occurred more often during this time, however, portrays a picture in which perceptions and reactions to the crisis hit their maximum when we began our surveys and declined more or less steadily thereafter, supporting our ability to examine a trajectory over time. In particular, Gallup polling spiked upward beginning with the collapse of Lehman Brothers and President Bush's bailout plan (September 15–20, 2008) as shown (see events 1 and 2 of Fig. 1). Concerns about the economy improved from early October to early November 2008 but failed to improve after that until mid-March 2009 (see events 4–9 of Fig. 1). For example, perceptions that the economy was getting worse hovered around 80% through March 2009. Reported weekly spending continued to deteriorate through this time period, decreasing by as much as 40%. Spending remained relatively constant after that but was far below pre-September levels. Unemployment continued to be a major worry with about 25% of the public reporting that employers were letting workers go. Remarkably, despite the magnitude and ubiquity of the crisis, public reaction to these events appears to have stabilized within about six months.

2. METHODS

2.1. Time Frame

Observing that major political and economic developments were unfolding, we launched this longitudinal panel study on September 29, 2008, the day the Dow experienced its largest one-day point drop. This was the first of seven waves of data collection dedicated almost exclusively to public response to the financial crisis. Further data collection followed on October 8, 2008, November 5, 2008, December 6, 2008, March 21, 2009, June 30, 2009, and October 6, 2009. We spaced the surveys closer together in the beginning of the study believing that the most change would occur early in the crisis and, of course, not knowing how long the crisis would last. Collecting seven waves of data over a year's period allowed time for the public to respond to different phases of the crisis. It also permitted a more thorough examination of the trajectory of this response.

2.2. Panel

A diverse panel of over 800 individuals participated in the study with more than 400 completing all seven waves of data. This ongoing Internet panel was developed by Decision Research through word-of-mouth and Internet recruiting (e.g., paying for Google search words). Nonrespondents (panelists invited to participate but who chose not to) did not differ significantly from respondents in terms of age, gender, or education. Surveys were left open for completion for four to six days, although most panelists responded in the first 24 hours. The response rate for each wave averaged 83%, with the lowest response rate being 74% (see Table I). These online panelists were paid at the rate of $15 per hour with a typical payment of $6 and an incentive if they completed all surveys. Any panelist who appeared to rush through the survey was eliminated and not invited to participate again. Typically, it took respondents about 20 minutes to answer the survey. Almost all respondents reported enjoying the surveys and they appeared to take them seriously. Demographic characteristics for the full panel at each wave appear in Table I. Throughout the study, there were more women than men due to the composition of our panel population. A typical respondent was about 39–40 years old with some college education and a household income of about $50,000 per year. Respondents who completed all seven surveys tended to be slightly older, more educated, more numerate, and had higher incomes than typical respondents in any given wave.

2.3. Questionnaire

Our online questionnaire consisted of up to 100 close-ended questions. In this article, we investigate the longitudinal relationships among perceived risk (to one's job, savings, investments, retirement), negative emotional reactions to the financial crisis (sadness, anxiety, fear, anger, worry, stress), confidence in the nation's leaders to manage the crisis (president, Congress, Treasury, and business leaders), and belief in one's ability to cope with the crisis. As a proxy for coping, we use a scale measuring belief that the crisis would limit one's ability to realize personal objectives (limited future prospects). This choice is discussed later in the article. We treat current mood state (a composite of negative and positive emotions) as a control variable. Gender,

Fig. 1. Perceptions of the economy, hiring, and reported spending (vertical axis on left indicates percentage of people reporting economy getting better, worse, or employers hiring or letting workers go; vertical axis on the right is the reported daily spending, not counting purchase of home, motor vehicle, or normal household goods). Copyright © 1999 Gallup, Inc. Reprinted with permission.

Table I. Demographic Characteristics of Sample Across Seven Waves

Variables	Completed All Waves	1	2	3	4	5	6	7
Age (years)	40.3	38.9	39.9	38.2	39.0	39.5	39.5	39.2
Gender (female)	68.8	71.1	70.2	64.8	64.7	64.7	66.7	66.4
Education (1–7)	5.2	5.0	5.0	5.0	5.0	5.1	5.0	5.1
Income (1–6)	4.4	4.3	4.3	4.3	4.4	4.4	4.3	4.4
Numeracy (range = 0–11 correct)	8.2	7.8	7.9	8.0	8.0	8.0	8.0	8.0
Political attitude (1–4)	2.5	2.52	2.52	2.52	2.52	2.52	2.51	2.50
Sample size	413	802	712	755	654	609	715	645
Percentage response rate	—	81	89	87	85	91	76	74

education, income, age, political attitude, and numeracy are treated as moderator variables. We also discuss briefly respondents' perceptions of the efficacy of two major legislative efforts, the rescue bill and the stimulus package. In Table II, we provide examples of a number of our questions and scales. We provide the questionnaires we used for each of the seven waves on our website.[6] Numeracy (ability to understand and use numeric information) was assessed in an earlier session with an 11-item scale developed by Lipkus, Samsa, and Rimer.[31]

2.4. Analytic Approach

2.4.1. *Descriptive Analysis*

We plotted both risk perception and negative emotion toward the financial crisis over the duration of the study to determine the shape of their trajectories. We then looked at risk perception and negative emotion over time for different levels of our moderating variables to investigate possible interactions. Finally, support for the rescue bill and the stimulus package are examined regarding their possible association to perceived risk.

2.4.2. *Latent Growth Curve Modeling*

To examine in a rigorous way how perceived risk changed over the duration of our study, we applied latent growth curve modeling to our data. Latent growth curve modeling applies a structural equation approach to longitudinal data that allowed us to investigate the trajectory of perceived risk.[32–34] This type of modeling was ideal for three reasons. First, it is comprised of a system of regression equations that allows an intercept representing initial levels of risk perception and a slope describing rates of change in risk perception to vary across individuals. It also allows the same to vary as a function of personal characteristics. This was important because we intended to investigate whether initial risk perception or rates of change were related to individual characteristics (e.g., gender and numeracy). Second, this approach allows regression coefficients associated with covariates such as negative emotion to vary over time. This was important because we sought to explain the trajectory of perceived risk on the basis of change in negative emotion, confidence in national leaders, and personal ability to cope with the crisis. Finally, this method of estimation controls for the autocorrelation and nonconstant variance likely to be present as we measured perceived risk and its covariates over time. This feature lent confidence that our slope estimates would be unbiased and our significance tests would be valid.

Model construction was guided by the need to anticipate the shape of the trajectory of perceived risk and to examine the contribution of our proposed covariates. Regarding the shape, recall that, because we began our study directly following the dramatic fall in the financial markets, perceived risk and negative emotions were likely to have been high at this point. The theory of hedonic adaptation predicts that negative emotions would begin to be nudged toward their baseline levels. To the extent that risk perception is the result of a negative emotional reaction,[5] perceived risk should follow suit. Hence, we were anticipating a downward trend in perceived risk to occur early in our study. In retrospect, we also came to believe that events during the study might have influenced the rate at which risk perception declined. As a result, we decided to fit a piecewise model pivoting around two key events: the election of Barack Obama in November 2008 and the beginning of the stock market rally in March 2009. This required that we estimate a model with three linear segments. Each of the three segments had their own regression slope (β_1, β_2, β_3) and a common intercept α.[34,35] If our predictions about the trajectory of perceived risk were correct, then all three slopes should be negative

[6] www.decisionresearch.org/people/burns.

Table II. Variable Table, Predicted Direction of Effects, and Internal Reliability (Cronbach's Alpha)

Variables	Description	Scale	Waves	Cronbach's Alpha
Dependent variable				
Risk perception index	Perceived risk of financial crisis to personal savings, investments, retirement, and job; average across 4 items (1 = *very low risk*; 2 = *low risk*; 3 = *moderate risk*; 4 = *high risk*; 5 = *very high risk*)	1–5	1–7	Average = 0.75, range across waves 0.71–0.80
	Time invariant variables (predicted effect on risk perceptions)			
Age	Respondent's age	Years	Prior	
Gender(–)[a]	Female = 0, male = 1	0–1	Prior	
Education	Grade school through graduate school	1–7	Prior	
Income	Under \$15K to \$75K plus	1–6	Prior	
Numeracy(–)	Numeracy scale from Lipkus, Samsa, and Rimer[(31)]	0–11	Prior	Average = 0.71
Political attitude	Scale representing political attitude with higher numbers being more liberal	1–4	Prior	
	Time varying variables (predicted effect on risk perceptions)			
Negative emotion index(+)	Emotional response to financial crisis comprised of anger, anxiety, fear, sadness, stress, and worry; average across six items.	1–4	1–7	Average = 0.91, range across waves 0.89–0.91
Limited future prospects(+)	Belief that opportunities to realize personal goals will be limited by crisis; higher numbers indicate opportunities more limited	1–4	1–7	
Confidence in Senator/President Obama, Congress, Treasury Secretary, or CEOs(–)	Separate scales each representing confidence in Senator/President Obama, Congress, Treasury Secretary, or CEOs to reduce the risk of the financial crisis; higher numbers indicate more confidence.	1–5	1–7	
Current mood state	Affect comprised of an average across ratings on five positive and five negative emotional states with higher numbers representing more positivity	1–5	3–7	Average = 0.81, range across waves 0.81–0.81

[a]Depicts the predicted relationship between the covariate and risk perception index.

and statistically significant. If, in addition, perceived risk declined more quickly at the beginning, β_1 would have the largest negative value.

To explain the changes in the trajectory of perceived risk, we also needed to estimate a regression slope (γ_{kt}) for each of our measures of negative emotion, confidence, and ability to cope. If our predictions about their contributions were correct, each of these should have the appropriate sign and be statistically significant. Finally, to explore the moderating influence of factors like gender and numeracy, we needed to consider both their influence on people's initial perceptions of risk ($\gamma_{\alpha q}$) as well as their influence on the change in perceived risk ($\gamma_{\beta q}$).

These modeling considerations are expressed in Equations (1)–(3). These equations describe risk perception on a case-wise basis for a typical person i. Components of these equations are discussed in brief here but are described in detail in the Appendix. Risk perception y_{it} varied over the seven time periods of our study. Time is represented by λ_{mt} and was coded in terms of months from the beginning of each segment with an initial value of zero. In Equation (1), perceived risk y_{it} for each person i on occasion t is a function of three sets of parameters and an error component. The first is an intercept α_i, which is a latent growth curve factor describing a person's initial level of perceived risk. The second are slopes β_{im}, which are latent growth curve factors depicting the trend of perceived risk for each segment. The third are slopes γ_{kt}, which describe the relationship of perceived risk with time-varying covariates w_{kit} during each time period. This equation has the typical form of a regression model, but there are two important differences. Notice that the intercept α_i and the slopes β_{im} are themselves functions of other parameters and covariates. It is this feature that allows initial risk perception and change in risk perception to be modeled as a function of individual characteristics. This point is discussed next.

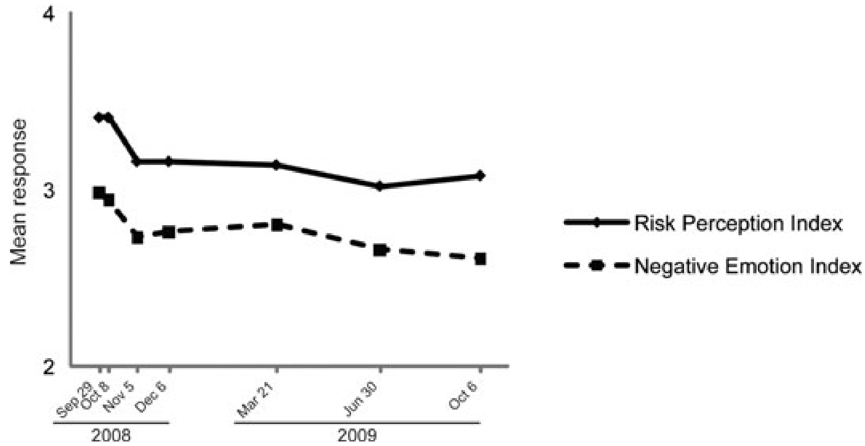

Fig. 2. Mean risk perception index (range = 1–5) and negative emotion index (range = 1–4) for panelists who completed all seven surveys ($N = 413$).

Equation (2) is also a regression model and its intercept α_i represents the initial level of perceived risk for person i and is a function of its intercept μ_α, time invariant factors x_{iq} such as gender, and a disturbance term $\varsigma_{\alpha i}$. If there are no covariates in the model then α_i simply equals the mean intercept (mean initial perceived risk) across all respondents. Similarly, Equation (3) is a regression model and its slope β_{im} represents the rate of change in perceived risk for person i and is a function of its intercept $\mu_{\beta m}$, time invariant factors x_{iq}, and a disturbance term $\varsigma_{\beta im}$. Similarly, if there are no covariates in the model then β_{im} simply equals the mean slope (mean rate of change) for all respondents. Variances for disturbance terms $\varsigma_{\alpha i}$ and $\varsigma_{\beta im}$, respectively, provide evidence of the extent to which individuals differ in their initial perceptions of risk and in their rates of change in perceived risk over time.[32] The larger the variance, the more individuals differ in their initial risk perception or their rate of change in perceived risk.

$$y_{it} = \alpha_i + \sum_{m=1}^{M} \beta_{im}\lambda_{mt} + \sum_{k=1}^{K} \gamma_{kt} w_{ikt} + \varepsilon_{it} \qquad (1)$$

$$\alpha_i = \mu_\alpha + \sum_{q=1}^{Q} \gamma_{\alpha q} x_{iq} + \zeta_{\alpha i} \qquad (2)$$

$$\beta_{im} = \mu_{\beta m} + \sum_{q=1}^{Q} \gamma_{\beta mq} x_{iq} + \zeta_{\beta im} \qquad (3)$$

Model estimation proceeded in two steps. Recall that we decided to fit a piecewise model with three segments because of the influence of the Obama election in November 2008 and the stock market rally beginning in March 2009.[7]

We first fit our piecewise model without covariates to examine how perceived risk changed over time and to compare the regression slopes for each of the three segments. If we had found no change in perceived risk, it would have been pointless to consider more complex modeling. We next introduced covariates into the model to see if we could account for the decline we observed in risk perceptions. Covariates that were measured over time such as a negative emotional reaction to the crisis were predicted to explain the decline in perceived risk. Covariates such as gender were included to explain differences in initial risk perceptions or differences in rates of decline in perceived risk based on individual characteristics. Model evaluation was based on different fit statistics and parameter estimation.

We used M*plus* software (version 6.0) to estimate all path coefficients, variances, correlations, and model fit parameters.[36] We also used an estimation routine that produced chi-square tests and standard errors that were robust to non-normality and nonindependence of observations.

3. FINDINGS

3.1 Plots of Risk Perception and Negative Emotion

The plot of risk perception and negative emotions is displayed in Fig. 2. Both risk perception and negative emotion appeared to move together and decline over time. Notably, both indices decreased

[7] We actually estimated both linear and quadratic models first but they did not fit well, and failed to capture the significant initial decline in the trajectory of negative emotions and perceived risk.

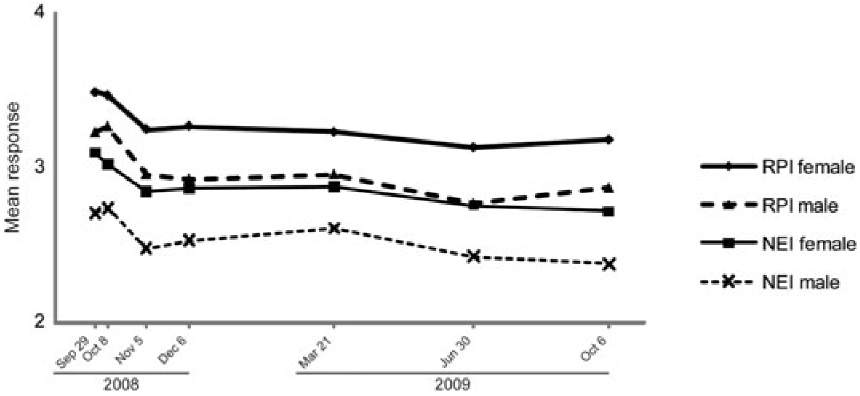

Fig. 3. Mean risk perception index (RPI; range = 1–5) and negative emotion index (NEI; range = 1–4) by gender for panelists who completed all seven surveys ($N = 413$).

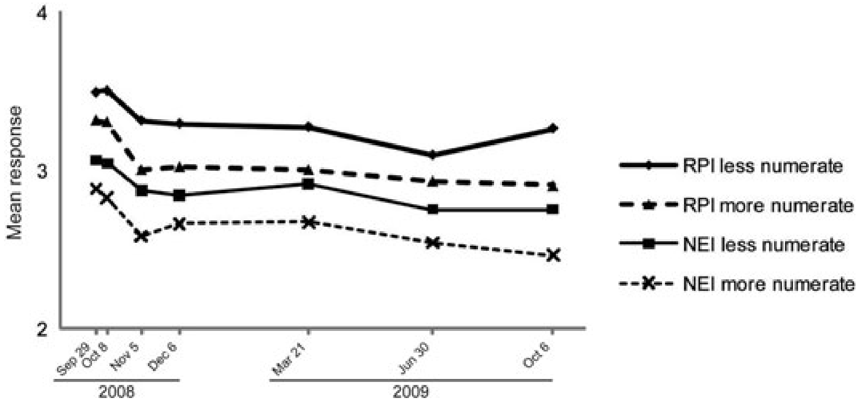

Fig. 4. Mean risk perception index (RPI; range = 1–5) and negative emotion index (NEI; range = 1–4) by numeracy for panelists who completed all seven surveys ($N = 413$).

sharply at the beginning, held steady from November 2008 to March 2009, and then declined further after that. Notice in Fig. 3 that women had higher perceived risk and as strong or stronger negative emotion about the financial crisis than did men at every point in the study. Less numerate people, as seen in Fig. 4, reported greater perceived risk and higher negative emotion across the entire time period compared to those who were more numerate. The less numerate also appear to have experienced a less steep decline in negative emotion and risk perceptions in the period leading up to November 2008.

3.2. Perception of Risk and Support for Obama and Congressional Actions

It appeared reasonable that initial declines in perceived risk were due in part to the historic election of Barack Obama running on a campaign of hope and change. To investigate this possibility (and determine whether we should retain piecewise modeling of the data), trajectories for perceived risk for different levels of political attitude, confidence in Obama, and emotional reaction to the Obama election are presented in Table III. Respondents who were conservative, who lacked confidence in Obama to fix the financial crisis, and who had a negative emotional reaction to his election had higher perceived risk during almost every wave than those of an opposing point of view who also reported steeper initial declines. It appears that Obama's election may have had an effect on the initial decline of perceived risk. In addition to this event effect, however, both

Table III. Means of Perceived Risk for Different Levels of Political Attitude, Confidence in Obama and Emotional Valence

Wave	Political Attitude (Conservative/ Liberal)	Confidence in Obama (Low/High)	Emotional Valence[a] (Negative/Positive)
9/29/08	3.48/3.51	3.55/3.46	3.52/3.44
10/08/08	3.45/3.44	3.51/3.41	3.49/3.43
11/05/08	3.27/3.17	3.36/3.16	3.35/3.17
12/06/08	3.28/3.19	3.33/3.21	3.37/3.20
3/21/09	3.25/3.14	3.30/3.15	3.34/3.17
6/30/09	3.23/3.02	3.29/3.03	3.28/3.03
10/06/09	3.30/2.98	3.25/3.07	3.26/3.13

[a]An index consisting of a list of four positive and four negative emotional reactions to Obama's election.

groups' perceived risk decreased. That is, even the people who appeared to believe that Obama's election would probably take the country in the wrong direction experienced a decline in perceived risk.

We also considered the possibility that the passage of the Emergency Economic Stabilization Act (TARP) on October 3, 2008 might have caused people to feel the crisis was being effectively handled. If true, this feeling could help explain the decrease in perceived risk. We queried our panel about whether Congress was right to pass this bill. On a 5-point scale ranging from *Congress was very wrong* to *Congress was very right* we found that 68.4% were either unsure or felt Congress was wrong to pass this bill. Most of our respondents did not support this legislation. Additionally, we compared the trajectories of perceived risk for those who did not support this bill with those who did. As we found with support for Obama, both groups experienced a decline in perceived risk. Here, however, both groups had approximately the same levels of perceived risk and rates of decline.

Risk perception also began to decline again in March 2009, following the stock market rally. We wondered what might be behind this small downward trend in perceived risk from March 2009 to October 2009. After all, perceived risk had not changed for several months. We first looked at the measures that comprised our risk perception index. This rally provided reason to be optimistic toward one's investments and perhaps retirement. Indeed, perceived risk toward investments and retirement did decrease during this period. The means for these two measures during this time period were 3.55, 3.43, 3.32 and 3.49, 3.40, 3.41, respectively. Conversely, by March unemployment was over 8% and would continue to rise to over 9% by the end of this period. Perceived risk towards jobs and savings showed no real change from March on. The means for these two measures were 2.89, 2.86, 2.85 and 2.77, 2.75, 2.78, respectively. It seemed, on balance, relief about retirement and investments slightly outweighed concerns about jobs.

We next wondered whether people who were optimistic about the stimulus package passed by Congress on February 17, 2009 would show a greater decline in perceived risk. We asked our panel how long they thought it would take for the stimulus package to begin improving the economy. On a 6-point scale ranging from *under six months* to *never*, we found 44.4% of respondents reported it would take longer than two years (15% said never). We compared the trajectories of perceived risk from March on, for those who indicated that the stimulus package would take less than two years to work, with those who said it would take longer to work, if at all. Perceived risk decreased for those who felt the stimulus package would take less than two years. Perceived risk actually increased for those who thought it would take longer than two years. These initial analyses reinforced our decision to estimate a piecewise model.

3.3. Piecewise Modeling

3.3.1. A Model with No Covariates

We first report the results from our piecewise model with no covariates (referred to as an unconditional model). The model we estimated was of the form $y_{it} = \mu_\alpha + \mu_{\beta 1}\lambda_{1t} + \mu_{\beta 2}\lambda_{2t} + \mu_{\beta 3}\lambda_{3t} + \varepsilon_{it}$, and its parameter estimates and fit statistics are given in Table IV. The intercept $\mu_\alpha = E(\alpha_i)$ was 3.51, representing respondents' average initial risk perception (where 3 was labeled *moderate risk* and 4 *high risk*), and suggesting people typically began with a moderate to high perceived risk. This is consistent with our study beginning at or near the peak of the crisis. The average slopes $\mu_{\beta m} = \mathrm{E}(\beta_{im})$ for the periods from September 29, 2008 to November 5, 2008, November 5, 2008 to March 21, 2009, and March 21, 2009 to October 6, 2009 were –0.21, –0.002, and –0.01, respectively. Hence, the model for the average person was $E(y_{it}) = 3.51 - 0.21\lambda_{1t} - 0.002\lambda_{2t} - 0.01\lambda_{3t}$. Notice that the decline in risk perception was much more pronounced during the first time segment than in the remaining time periods. These estimates suggest that perceived risk trended downward most quickly during the first five weeks, plateaued for several months, and then began to gradually decline thereafter. The first slope is statistically significant, the second slope is not significant, and the third slope cannot be determined (its variance had to be fixed to zero for estimation reasons). The trajectory this model describes is quite consistent with Figs. 2–4. It is also consistent with the predictions of hedonic adaptation, assuming risk perception is related to negative emotion, which we examine shortly. A trajectory remarkably similar to this was observed in the system dynamics modeling conducted by Burns and Slovic,[13] in which they simulated public response to different types of crises.

Variation in this piecewise model about the intercept α_i (initial perceived risk) was 0.53 and

Table IV. Parameter Estimates and Fit Statistics for Four Latent Growth Curve Models

	Piecewise	Piecewise with Covariates
Growth Curve	Unconditional	Conditional Model:
Intercepts and Slopes	Model	Time Invariate and Time Varying Covariates
Intercept $\mu_\alpha/E(\alpha_i)$	*3.51***	*1.90***
Slope1 $\mu_{\beta 1}$/E(β_{i1})	0.21**	−0.07
Slope2 $\mu_{\beta 2}$ /E(β_{i2})	0.002	0.01
Slope3 $\mu_{\beta 3}$/E(β_{i3})	−0.01**	−0.01
Time Invariate x_{iq}	—	Regression coefficients: intercept, slopes 1–3
Gender (Male; $q=1$)[a]		$\gamma_{\alpha q}/\gamma_{\beta 1\mathrm{q}}/\gamma_{\beta 2\mathrm{q}}/\gamma_{\beta 3\mathrm{q}}$
Numeracy ($q=2$)		*0.0*/0.02/–0.02/–0.01
Income ($q=3$)		*−0.02**/–0.01/0/0
Age ($q=4$)		*−0.03**/0.01/–0.01/0.01
Education ($q=5$)		*0*/0.01*/0/0
Political Attitude (Liberal; $q=6$)		*−0.01*/0.02/0/0
		0.03/–0.04/–0.01/–0.02*
Time Varying w_{ikt}	—	Regression coefficients: time periods 1–7
NegEmotionIndex ($k=1$)[b]		$\gamma_{\mathrm{k}1}-\gamma_{\mathrm{k}7}$
LimitedFutureProspects ($k=2$)		0.37**/0.35**/0.30**/0.30**/0.36**/0.24**/0.32**
ConfidenceObama ($k=3$)		0.18**/0.22**/0.25**/0.22**/0.19**/0.27**/0.26**
ConfidenceCongress ($k=4$)		0.02/−0.01/−0.01/0/0.02/−0.02/0
ConfidenceTreasury ($k=5$)		−0.08**/−0.03/0/−0.01/0.02/−0.04/0.04
ConfidenceCEO ($k=6$)		0.03/0.02/0.02/0.03/−0.07/−0.07/−0.04
CurrentMoodState ($k=7$)		0.03/−0.02/−0.01/−0.02/−0.03/−0.02/−0.07
		na/na/−0.01*/0/0/−0.01/0
R^2 (y_{it})	Range 0.62–0.71	Range 0.60–0.69
Fit Statistics		
χ^2	19.6	483.3***
	$df=18$	$df=318$
CFI	0.99	0.95
SRMR	0.02	0.03

[a]Index q represents the qth time invariant covariate (1–6).
[b]Index k represents time the kth varying covariate (1–7).
*$p<0.05$, **$p<0.01$.
Notes: Models with and without covariates are presented. Piecewise models have a slope (β_{im}) for each of three linear segments. To distinguish between intercepts and slopes all estimates having to do with model intercepts have been italicized. As an illustration consider the piecewise model with covariates. To provide the reader with estimates for all components of Equations (1)–(3) we must sometimes include multiple estimates in a cell. Beginning from top to bottom, notice that $E(\alpha_i)$ is 1.90, which is the outcome of Equation (2) and now the intercept α used in Equation (1) for a typical person. Similarly, $E(\beta_{i1})$ is –0.07, which is the outcome of Equation (3) and the slope term β_1 (for piece 1 representing the first time segment September to November 2008) used in Equation (1) for a typical person. The two remaining slope coefficients $E(\beta_{i2})$ and $E(\beta_{i3})$ are 0.01 and –0.01, respectively. They are also used in Equation (1) as β_2 (piece 2 representing November 2008 to March 2009) and β_3 (piece 3 representing March to October 2009). *Notice that the index i has been suppressed for α and β_m because we averaged across respondents. After obtaining our regression estimates we averaged across individuals by inserting mean values for all covariates. We could have, by substituting individual responses into Equations (2) and (3), obtained a separate Equation (1) for each person.* The intercept α_i and three slopes β_{im} were regressed on all x_{iq}. Consider the first time invariant covariate gender. For the intercept α_i the regression coefficient $\gamma_{\alpha 1}$ was effectively 0 and for slopes $\beta_{i1}, \beta_{i2}, \beta_{i3}$ the regression coefficients $\gamma_{\beta 11}, \gamma_{\beta 21}, \gamma_{\beta 31}$ were 0.02, −0.02,−0.01, respectively. y_{it} was regressed on α_{I}, β_{i1}, β_{i2}, β_{i3} and on the time varying covariates w_{ikt}. Now we have seven regression coefficients in a cell, one for each data collection wave. Consider the first time varying covariate Negative Emotion Index (w_{i1t}). The regression coefficients $\gamma_{11}-\gamma_{17}$ for negative affect were 0.37, 0.35, 0.30, 0.30, 0.36, 0.24, and 0.32, respectively. During the first wave γ_{11} was 0.37, which describes the relationship between negative emotion and risk perception for wave one. Similarly, R^2 was computed for y_{it} with values ranging from 0.60 to 0.69. Fit statistics (χ^2, CFI, SRMR) indicate how well this model fits the data overall.

variances for the slopes β_{im} (rates of change in perceived risk) were 0.1 and 0.01 for the first two time segments ($V(\beta_{i3})$ was constrained to zero). Ratios of variance estimates to their standard errors indicated people differed much more in their initial levels of perceived risk than in the rate in which their perceived risk declined. The most variation in people's trajectories occurred during the first time segment. The intercept and three slopes did a reasonable job explaining perceived risk, with R^2 ranging from 0.61

to 0.71 across the seven data waves. Looking at the three fit indices, this model fit the data extremely well, lending confidence to the belief that the November election and the March stock market rally were pivotal events helping to shape the rate of decline in perceived risk.

In brief, this model suggests the following. Overall, risk perception declined quickly in the beginning and then tapered off, respondents differed in their initial perceptions of risk but much less in their rate of decline, and that two pivotal events appear to have influenced the trajectory of this decline. To understand what factors may have been associated with the trajectory of perceived risk, we next discuss a latent growth curve model with covariates (referred to as a conditional model).

3.3.2. Piecewise Modeling with Covariates

We introduced covariates into the model just described. The model we estimated now was of the form $y_{it} = \alpha_i + \beta_{i1}\lambda_{1t} + \beta_{i2}\lambda_{2t} + \beta_{i3}\lambda_{2t} + \Sigma\gamma_{kt}w_{ikt} + \varepsilon_{it}$, and parameter estimates and fit statistics are given in Table IV. The latent growth curve intercept $E(\alpha_i)$ was 1.90 and the latent growth curve slopes $E(\beta_{im})$ were –0.07, 0.01, and –0.01. These estimates now take into account the time invariant covariates x_{iq} (such as gender) and the effect of the time varying covariates w_{ikt} (such as negative emotions). Hence, the model for the average person was $E(y_{it}) = 1.90 - 0.07\lambda_{1t} + 0.01\lambda_{2t} - 0.01\lambda_{3t} + \Sigma\gamma_{kt}\mathrm{w}_{\mathrm{kt}}$. A cursory inspection of this model suggests that from September 29, 2008 to November 5, 2008 perceived risk trended downward, from November 5, 2008 to March 21, 2009 it trended slightly upward, and from March 21, 2009 to October 6, 2009 it trended slightly downward. However, a comparison of these coefficients with those of the previous model is instructive. Now only the intercept is statistically significant. Notice that in the unconditional model the first slope was –0.21, but with the inclusion of covariates it is now only –0.07. This suggests that the covariates explained part of the change in risk perceptions.

In particular, we discovered that the covariates, negative emotion index and limited future prospects, accounted for the decrease in perceived risk, especially during the initial time period. As shown in Table IV, negative emotion index and limited future prospects were significantly related to perceived risk for all seven waves of data. An increased negative emotional reaction to the crisis and a belief that the crisis would limit one's opportunities to realize personal objectives were associated with increased perceived risk. This was not true for our confidence measures. Only confidence in Congress's ability to manage the crisis during the first wave was found to be significantly associated with decreased perceived risk. Current mood state was included as a control for incidental feelings and had a significant relationship with perceived risk only when it was first introduced during the third wave of data collection (with more negative moods being associated with greater perceived risk). To test further whether it was primarily respondents' negative emotional reaction to the crisis and their belief that the crisis would limit their opportunities to realize their objectives that accounted for the downward trend in perceived risk, we temporarily eliminated them from our model. The intercept and the first slope for this revised model returned to the levels previously observed in the unconditional model. It appeared that emotional reaction to the crisis and a belief in its impact on future prospects were central in accounting for the decline in perceived risk. To determine which had the larger impact, we removed each from the model individually. Negative reaction to the crisis almost completely accounted for the initial downward trend, and hence played the larger role. It also had larger regression coefficients than the covariate limited future prospects, as shown in Table IV.

Although we chose to model negative emotion as an index of six emotions, we also modeled each of the negative emotions separately to determine their relationship to perceived risk over time. All were positively related to perceived risk. Fear, anxiety, and worry were the most predictive of perceived risk with median partial correlations of 0.23, 0.21, and 0.20, respectively, after controlling for confidence, belief about future prospects, and current mood. Anger and sadness were the least predictive, with median partial correlations of 0.11 and 0.16, respectively.

We were also able to investigate, as part of our estimation of this conditional model, whether individual characteristics were associated with respondents' initial perceptions of risk and their rate of change in perceived risk. Previous studies have found women to perceive greater risk than men across a variety of products and events. Fig. 3 indeed suggests that women had higher perceived risk than men throughout the study. However, model estimates showed gender to have no significant relationship to initial perceived risk nor to rates of change in perceived risk. Past research had found numeracy to be negatively associated with perceived risk.[2,37]

Fig. 4 suggests that less numerate respondents had higher perceived risk throughout the study. Model estimates indicate that less numerate respondents did have a higher initial perceived risk but did not differ in their rate of change in perceived risk. Higher income was also associated with lower initial perceived risk. Only age and political attitude were associated with rates of change in perceived risk. Risk perceptions of older respondents trended downward from September to November 2008 more quickly than those of younger respondents. Similarly, risk perceptions for more conservative respondents from March to October 2009 trended downward more quickly than for less conservative respondents.

Variation in this model about the intercept α_i (initial perceived risk) was 0.26 and variances for the slopes β_{im} (rates of change in perceived risk) were 0.07, 0.01 ($V(\beta_{i3})$ was constrained to zero). Notice that the variance for the intercept is now only half as large as in the previous model (0.26 down from 0.53). Personal characteristics such as numeracy and income helped explain variation in respondents' initial risk perception. Ratios of variance estimates to their standard errors indicated people differed more in their initial levels of perceived risk than in the rate in which their perceived risk declined. The most variation in people's trajectories occurred during the first time segment. The intercept, three slopes, and covariates did a reasonable job explaining perceived risk, with R^2 ranging from 0.60 to 0.69 across the seven waves of data. This model fit well. The comparative fit index was 0.95 and the standardized root mean square residual (SRMR) was 0.03.

In brief, this modeling suggests the following. We first observed in the unconditional model that perceived risk did indeed decrease during our study and that this decline was greatest in the beginning. We also noted that respondents differed in their initial perceived risk but differed much less in their rates of decline. With the conditional model, we added variables representing personal characteristics as well as variables that changed over time. We observed that numeracy and income helped explain respondents' initial perceived risk, but gender did not. We also learned that a negative emotional reaction to the crisis and a belief that the crisis would limit one's ability to realize personal objectives were consistently associated with increased perceived risk. Conversely, confidence in the nation's leaders to effectively manage the crisis was not associated with perceived risk.

4. DISCUSSION

4.1. Decay of Perceived Risk

We set out to learn how perceived risk might change amidst an ongoing crisis. Our study began during a dramatic fall in the financial markets. This led us to postulate that, consistent with a process of hedonic adaptation, negative emotions such as fear, anger, and worry regarding the crisis would decline toward precrisis baseline levels. This decline we reasoned would be accompanied by a decrease in perceived risk given previous research finding a tight link between negative emotion and risk perceptions.[38] We also thought that confidence in how the crisis was being handled by national leaders and confidence in one's own ability to adjust would be predictive of less perceived risk. Based on prior literature, we hypothesized that people's initial perceived risk and their rate of decrease in perceived risk might be influenced by personal characteristics such as gender and numeracy.

Graphing the means of negative emotion and perceived risk over an entire year indicated that there was indeed a decline in these two variables. By inspection, it was clear that the steepest decline in perceived risk occurred initially during the period leading up to the presidential election. From early November 2008 to late March 2009, we saw little or no change in perceived risk and from March to October 2009, we saw risk perception decline and then rise slightly. This pattern was remarkably close to the Gallup polling shown in Fig. 1, which depicted concern for the economy and related consumer spending, and lessened our concern that we had captured special moments in time rather than a trajectory. Confidence in national leaders followed a different pattern. From September 2008 through December 2008, confidence increased in the nation's leaders but decreased after that. This pattern may have been due to a gradual realization that this crisis was more complex than first imagined and a growing concern over rising unemployment. Conversely, people's belief in their ability to adjust and realize personal objectives steadily increased.

Our latent growth curve modeling began without including any of the covariates just described so we could examine the trajectory of risk perception in isolation. This more rigorous analysis confirmed that perceived risk declined over the course of our study. This finding was consistent with our predictions based on hedonic adaptation. We also saw from our modeling that most of the decline occurred from September 2008 to November 2008. Some researchers have proposed that the rate of decline in negative emotions may be proportional to the gap between current and baseline levels.[(23)] Because our study began when negative emotions were high, this gap was most likely large. As respondents adapted to the crisis, this discrepancy should shrink (according to the theory) and thus slow the rate of decline in negative emotions (and, by association, perceived risk). We also observed that respondents differed significantly in their initial risk perceptions but much less in their rate of change in perceived risk. This finding suggests that, while people may have differed markedly in their initial reactions to the crisis, their return toward baseline levels showed far less variation. We did observe, however, that individuals who differed in age and political attitude had somewhat different risk perception trajectories. Numeracy and income helped explain differences in initial reactions. Graphical analysis suggested women had higher perceived risk than men but our model results did not. The lack of a statistical difference in initial perceived risk between men and women may have been a statistical artifact. We had a much smaller sample size for men than women, which reduced the power of the corresponding statistical test in our model.

To understand what was behind the decline in perceived risk, we introduced covariates into the latent growth curve model. We found that a negative emotional reaction to the financial crisis was highly predictive of heightened perceived risk. In fact, and consistent with work on the affect heuristic and the risk-as-feelings framework,[(38,39)] it was easily the most predictive factor and accounted for a substantial portion of the downward trend in risk perception. Our findings suggest that this crisis was a deeply emotional experience for people, but that most began to adapt quickly despite the lack of encouraging news about the economy.

We also found a belief that the financial crisis would limit opportunities to realize personal objectives to be predictive of heightened perceived risk. It accounted for a portion of the downward trend in perceived risk. This measure was used in the present study as a proxy for one's belief in the ability to cope with the crisis.[8] However, due to the nature of the financial crisis, beliefs about the ability to realize personal objectives may be a reasonable measure of coping. The financial crisis was ubiquitous in its effects and almost everyone faced economic challenges. If an individual felt that he or she could still realize personal goals, it most likely was based on an assessment of convictions, skills, and personal support system. Unlike confidence in national leaders, belief in the ability to realize personal objectives increased steadily, implying that most people were learning to cope with the crisis.

We did not find that confidence in the nation's leaders to manage the crisis was predictive of perceived risk. Confidence in President Obama, Congress, the Treasury Secretary, and business leaders were all included in our latent growth curve model. The fact that these measures were not highly correlated with perceived risk was a surprise. There are at least three possible explanations for this. First, perceived risk was measured on a scale that focused on specific personal vulnerability to the crisis in terms of jobs, investments, and retirement. Conversely, confidence in national leaders was measured on a scale that focused on competence to manage the crisis at the national level, and did not refer to specific attributes of the crisis. This difference in focus may have reduced the relevance of our confidence measure for perceived personal risks. Second, unlike a natural disaster, technological accident, or terrorist attack, how best to address the financial crisis was poorly understood. Almost three years later, there is still little agreement on whether the rescue bill and stimulus package have improved the economy. Respondents may have had a difficult time making this assessment and connecting it to their own lives. Third, negative emotions could have played a mediating role in the relationship between confidence and perceived risk. Simple correlations between our confidence measures and perceived risk were all negative as predicted, and for Congress, the Treasury Secretary, and business leaders were also statistically significant. However, after controlling for negative emotions the partial correlations between these confidence measures and perceived risk were much smaller and statistically insignificant.

We speculated that pivotal events may have also influenced this trajectory and most particularly the steep initial decline. This possibility led us to

[8]We first attempted to include measures that dealt directly with feelings of uncertainty and a lack of personal control with regard to the crisis. These proved to be only modestly related to perceived risk. We also tried a variable that asked about one's ability to adjust to the crisis, but this inexplicably caused estimation problems in our model.

construct a piecewise latent growth curve model. Certainly, it is reasonable to think that the anticipation of Barack Obama's historic election, combined with his campaign message of hope and change, may have contributed to the pronounced decrease in perceived risk and negative emotion during this period. As we acknowledged earlier, this appears to have been the case. However, we also argued that even the risk perceptions of respondents who clearly were not supporters of Obama or his policies declined. For this reason, we believe that hedonic adaptation and increased community support and reassurance played more significant roles in this decline. However, perceived risk did not continue to decline from November 2008 to March 2009. A possible explanation is that, in the absence of any good news about the economy following the election, risk perception remained steady until March. Recall that in early December 2008 came the official announcement that the United States had been in a recession since 2007. Similarly, in mid-December the public learned of the massive fraud by Bernard Madoff. These stories together with continued losses in the stock market and rising unemployment may have arrested the decline in negative emotions and perceived risk. The stock market rally in mid-March 2009 probably provided the first glimmer of economic recovery, causing perceived risk to decline again. Even this decline was very modest in comparison with the period from September to November 2008.

However, there may be an additional explanation for why we did not see much decline in either negative emotion or perceived risk since November 2008. If as argued above, respondents' decline in either negative emotion or perceived risk was proportional to the gap between their peak and baseline levels, then we would expect to see such a slowing of decline as the gap became smaller over time. Although negative emotions and perceived risk experienced only a modest decline from November 2008 on, we also did not see any significant increases in negative emotion or perceived risk in response to a number of sobering reports about the economy. Solomon[18] has argued that the speed with which negative emotions return to their baseline levels increases with repeated exposure to adverse stimuli. Perhaps our respondents improved in their ability to regulate their emotional reaction to these grim news stories. Their reported ability to realize their personal objectives and to adjust to the crisis steadily increased over the course of the study.

4.2. Future Directions

We have tracked the trajectory of risk perception amidst an ongoing crisis and have examined factors that appear related to initial levels of perceived risk and changing levels over time. However, we collected additional data that also looked at behaviors and even perceptions of other types of disasters. A logical next step is to connect perceived risk with risk-related activities such as the investment and purchase behaviors that our respondents reported during this time period. Similarly, comparing responses to the financial crisis with other types of disasters may shed light on differences across events. For example, would we see the same pattern of decline in negative emotion and perceived risk in other types of crises?

Our analysis focused primarily on aggregate response. However, we noticed that some respondents had markedly different response trajectories. If we are to further understand how hedonic adaptation operates amidst a crisis, we need to look more closely at how individuals return to precrisis baseline levels—or return to new baseline levels. For example, higher perceived risk among less numerate individuals may be due to their lesser use of numeric information and greater use of nonnumeric and often emotional sources of information.[40] It is not known whether less numerate individuals might have had stronger emotional reactions to a crisis but relied on these reactions to the same extent as the highly numerate throughout the crisis to form risk perceptions or whether the less numerate simply relied more on emotional reactions. Identifying clusters of people who respond similarly during a crisis would also help in our design of risk communications. This could be accomplished through latent class modeling.

To deepen our understanding of how risk perception changes in response to a disaster, we need to collect longitudinal data at a higher level of granularity than we did in this study. First, we need to regularly collect data on a wide variety of risks to establish baselines for emergent crises. One of the major challenges we faced in this study was not knowing what people's baseline levels of emotion and perceived risk were. Second, we need to collect enough waves of data immediately following the peak of the crisis to precisely estimate people's response function.

4.3 Conclusions

Our results suggest that, in general, people's perceptions of risk appear to decrease most rapidly during the initial phase of a crisis and then begin to level off after that. Even in the presence of persistent and grim news lasting several months, this was true in our study. Similarly, this decline also seems to be associated with a decrease in negative emotion toward the crisis and an increased belief that one can still realize personal objectives. We have offered possible explanations for this observation. Most promising is the possibility that negative feedback mechanisms, both psychological (hedonic adaptation) and sociological (community support), may nudge perceived risk back to baseline levels during and following a crisis. Emotion appears to be the key player in this process. Ordinarily, returning to baseline levels is helpful to resuming normal activities, particularly when the risks are being well managed. (Of course, sometimes it is not an appropriate adjustment to risk as when patients stop monitoring their health once symptoms disappear or let their insurance policies lapse following a disaster.) Finally, our results demonstrate that groups may experience a crisis differently depending on a combination of personal characteristics such as income and numeracy as well as age and political attitudes.

According to Sellnow *et al.*,[41] effective risk policy during a crisis should engage in communications that have the right content and are appropriately timed. Our findings suggest that, even amidst a crisis, perceived risk is likely to decline quickly. That is, how the public reacts a few days into the crisis may be very different than how they will respond a few weeks later. Policymakers would do well to reflect on this point, and perhaps wait before they appear on national media speculating about new risks and calling for wide, sweeping investigations. Similarly, they should be cautious about inciting negative emotions such as fear or undermining people's ability to adjust to the crisis. These actions may needlessly increase perceptions of risk. Consider the urgent calls by some elected officials for increased regulation of the U.S. nuclear power industry immediately following the Japanese nuclear disaster in March 2011. Discussions of nuclear safety are fine, but public discourse would have been more nuanced a few weeks later, after the public had calmed down. Risk management and communication should work in sync with the emotional and social mechanisms we have discussed, as well as people's tendency to adapt and return to normal.

ACKNOWLEDGMENTS

This research was supported by the National Science Foundation under grant numbers SES-0728934, SES-0820197, and SES-0901036. Any opinions, findings, and conclusions or recommendations in this document are those of the authors and do not necessarily reflect views of the National Science Foundation. Additionally, this research was also supported by the U.S. Department of Homeland Security through the National Center for Risk and Economic Analysis of Terrorism Events (CREATE) under award number 2010-ST-061-RE0001. However, any opinions, findings, and conclusions or recommendations in this document are those of the authors and do not necessarily reflect views of the U.S. Department of Homeland Security, or the University of Southern California, or CREATE. We are grateful for the many helpful suggestions offered by reviewers. Daniel Västfjäll also provided an insightful review of our article. Dale Glaser provided technical assistance with our growth curve modeling for which we are very grateful.

APPENDIX

DEFINITIONS OF TERMS IN EQUATIONS AND MODEL

Variables/ Coefficients	Index	Interpretation
y_{it}	$i = 1 - N_t$ $t = 1 - 7$	Risk perception value for *i*th person at time *t*. It's a function directly or indirectly of all that follows in this table.
α_i	$i = 1 - N_t$	Underlying intercept for *i*th individual. It reflects the person's initial level of risk perception. Latent growth factor anchoring underlying change in risk perception. A random coefficient so possibly a function of time invariant covariates (e.g., gender).
β_{im}	$i = 1 - N_t$ $m = 1 - 3$	Underlying slope for *i*th person. Every model has three piecewise linear terms. Latent growth factor representing change in risk perception over time (measured in months). A random coefficient and possibly a function of time invariant covariates.
λ_{mt}	$m = 1 - 3$ $t = 1 - 7$	Time coefficient for the *m*th slope at time *t*. Here it is measured in fractions of months from the beginning of each of three time segments. For example, $\lambda_{m1} = 0$.
γ_{kt}	$k = 1 - 7$ $t = 1 - 7$	Slope coefficient for *k*th time varying covariate at time *t*.
w_{ikt}	$i = 1 - N_t$ $k = 1 - 7$ $t = 1 - 7$	Value for *k*th time varying covariate (e.g., negative emotional index) for *i*th person at time *t*. Represents a time specific association with risk perception. Together with α_I and β_{im}, w_{ikt} accounts for variation in risk perception.
ε_{it}	$i = 1 - N_t$ $t = 1 - 7$	Residual term representing error in predicting risk perception for *i*th person at time *t*. Its variance measures *within*-person variability in risk perception across time.
μ_α	n/a	Intercept in Equation (2). Average initial status of risk perception across all respondents for $\lambda_{m1} = 0$ and no covariates in model.
$\gamma_{\alpha q}$	$q = 1 - 6$	Slope coefficient for *q*th time invariant covariate predicting α_i.
x_{iq}	$i = 1 - N_t$ $q = 1 - 6$	Value for *i*th person on *q*th time invariant covariate (e.g., numeracy). Accounts for variation in intercept $\alpha_{i.}$
$\zeta_{\alpha i}$	$i = 1 - N_t$	Disturbance term representing error in predicting the intercept for the *i*th person. Its variance measures *between*-person variability in initial risk perception.
$\mu_{\beta m}$	$m = 1 - 3$	Intercept in Equation (3). Average rate of change in risk perception across all respondents with no covariates in model.
$\gamma_{\beta q}$	$q = 1 - 6$	Slope coefficient for *q*th time invariant covariate predicting β_{im}.
$\zeta_{\beta im}$	$i = 1 - N_t$ $m = 1 - 3$	Disturbance term representing error in predicting the *m*th slope for the *i*th person. Its variance measures *between* person variability in the rate of change in risk perception.

REFERENCES

1. Breakwell GM. The Psychology of Risk. UK: Cambridge University Press, 2007.
2. Dieckmann NF, Slovic P, Peters EM. The use of narrative evidence and explicit likelihood by decisionmakers varying in numeracy. Risk Analysis, 2009; 29(10):1473–1488.
3. Cvetkovich G, Siegrist M, Murray R, Tragesser S. New information and social trust: Asymmetry and perseverance of attributions about hazard managers. Risk Analysis, 2002; 22:359–367.
4. Slovic P (ed). The Perception of Risk. London: Earthscan, 2000.
5. Slovic P (ed). The Feeling of Risk: New Perspectives on Risk Perception. London, UK: Earthscan; 2010.
6. Mendes E, Morales L. (2009). The decade in review: Four key trends, 2009. Available at: http://www.gallup.com/poll/124787/Decade-Review-Four-Key-Trends.aspx, Accessed on July 29, 2010.
7. Flynn J, Peters E, Mertz CK, Slovic P. Risk, media, and stigma at rocky flats. Risk Analysis, 1998; 18(6):715–727.
8. Sheppard B. The Psychology of Strategic Terrorism: Public and Government Responses to Attack. London: Routledge, 2009.
9. Prager F, Asay GRB, Lee B, von Winterfeldt D. Exploring reductions in London underground passenger journeys following the July 2005 bombings. Risk Analysis, 2011; 31(5):773–786.
10. Kasperson RE, Renn O, Slovic P, Brown HS, Emel J, Goble R. The social amplification of risk: A conceptual framework. Risk Analysis, 1988; 8:177–187.
11. Burns WJ, Slovic P, Kasperson RE, Kasperson JX, Renn O, Emani, S. Incorporating structural models into research on the social amplification of risk: Implications for theory construction and decision making. Risk Analysis, 1993; 13:611–623.
12. Pidgeon N, Kasperson RE, Slovic P. The Social Amplification of Risk. UK: Cambridge University Press, 2003.
13. Burns WJ, Slovic, P. The diffusion of fear: Modeling community response to a terrorist strike. Journal of Defense Modeling and Simulation: Applications, Methodology, Technology, 2007; 4(4):1–20,

14. Siegrist M. The influence of trust and perceptions of risks and benefits on the acceptance of gene technology. Risk Analysis, 2000; 20(2):195–203.
15. Slovic P. Trust, emotion, sex, politics, and science: Surveying the risk-assessment battlefield. Risk Analysis, 1999; 19:689–701.
16. Carver CS, Scheier MF. On the Self-regulation of Behavior. UK: Cambridge University Press, 1998.
17. Frederick S, Loewenstein G. Hedonic adaptation. Pp. 302–329 in Kahneman D, Diener E, Schwarz N (eds). Well-being: The Foundations of Hedonic Psychology. New York: Russell Sage Foundation, 1999.
18. Solomon RL, Corbit JD. An opponent process theory of motivation: Temporal dynamics of affect. Psychological Review, 1974; 81(2):119–145.
19. Solomon RL. The opponent-process theory of acquired motivation: The costs of pleasures and the benefits of pain. American Psychologist, 1980; 35(8):691–712.
20. Suomi, SJ. Primate separation models of affective disorder. Pp. 195–214 in Madden J, J IV (ed). Neurobiology of Learning, Emotion, and Affect. New York: Raven Press, 1991.
21. Hemenover, SH. Individual differences in rate of affect change: Studies in affective chronometry. Journal of Personality and Social Psychology. 2003; 85:121–131.
22. Chow, SM, Ram, N, Boker, SM, Fujita, F, Clore, G. Emotion as a thermostat: Representing emotion regulation using a damped oscillator model. Emotion, 2005; 5(2): 208–225.
23. Boker, SM, Montpetit, MA, Hunter, MD, Bergeman, CS. Modeling resilience with differential equations. Pp. 183–206 in Molenaar PCM, Newell KM (eds). Individual Pathways to Change. Washington, DC: American Psychological Association, 2010.
24. Lerner JS, Keltner D. Beyond valence: Toward a model of emotion-specific influences on judgment and choice. Cognition & Emotion, 2000; 14:473–493.
25. Siegrist M, Gutscher H, Earle T. Perception of risk: The influence of general trust, and general confidence. Journal of Risk Research, 2005; 8(2):145–156.
26. Siegrist M, Earle TC, Gutscher H. Test of a trust and confidence model in the applied context of electromagnetic field (EMF) risks. Risk Analysis, 2003; 23:705–716.
27. Finucane ML, Slovic P, Mertz CK, Flynn J, Satterfield TA. Gender, race, and perceived risk: The “white male” effect. Health, Risk, & Society, 2000; 2(2):159–172.
28. Peters E, Hibbard JH, Slovic P, Dreckmann NF. Numeracy skill and the communication, comprehension, and use of risk-benefit information. Health Affairs, 2007; 26:741–748.
29. Behravesh N. Spin-Free Economics: A No-Nonsense Guide to Today’s Global Economic Debates. New York: McGraw Hill, 2009. Pp. 313–317.
30. Jones JM, Newport F, Saad L. A year of economic unease: Long way to go to recover, 2009. Available at: http://www.gallup.com/poll/122933/Year-Economic-Unease-Long-Way-Recover.aspx, Accessed on July 29, 2010.
31. Lipkus IM, Samsa G, Rimer BK. General performance on a numeracy scale among highly educated samples. Medical Decision Making, 2001; 21:37–44.
32. Singer JD, Willett JB. Applied Longitudinal Analysis. New York: Oxford University Press, 2003.
33. Acock AC. Latent curve analysis: A manual for research data analysts, 1999. Available at: http://oregonstate.edu/dept/hdfs/papers/lgcmanual.pdf, Accessed on July 8, 2010.
34. Bollen KA, Curran PJ. Latent Curve Models: A Structural Equation Perspective. Hoboken, NJ: John Wiley & Sons, 2006.
35. Preacher KJ, Wichman AL, MacCallum RC, Briggs NE. Latent Growth Curve Modeling. Los Angeles, CA: Sage Publications, 2008.
36. Muthen LK, Muthen BO. Mplus User’s Guide. Fifth Edition. Los Angeles, CA: Muthen & Muthen, 1998–2007.
37. Lipkus IM, Peters EM, Kimmick G, Liotcheva V, Marcom P. Breast cancer patients’ treatment expectations after exposure to the decision aid program, Adjuvant Online: The influence of numeracy. Medical Decision Making, 2010; 30(4), 464–473.
38. Loewenstein G, Weber EU, Hsee CK, Welch N. Risk as feelings. Psychological Bulletin, 2001; 127:267–286.
39. Slovic P, Finucane ML, Peters E, MacGregor DG. The affect heuristic. Pp. 397–420 in Gilovich T, Griffin D, Kahneman D (eds). Heuristics and Biases: The Psychology of Intuitive Judgment. New York: Cambridge University Press, 2002.
40. Peters E. Beyond comprehension: The role of numeracy in judgments and decisions. Current Directions in Psychological Science, in press.
41. Sellnow TL, Ulmer RR, Seeger MW, Littlefield RS. Effective Risk Communication: A Message-Centered Approach. New York: Springer, 2009.