*Risk Analysis, Vol. 34, No. 6, 2014* DOI: 10.1111/risa.12149

# An Assessment of Change in Risk Perception and Optimistic Bias for Hurricanes Among Gulf Coast Residents

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This study focuses on levels of concern for hurricanes among individuals living along the Gulf Coast during the quiescent two-year period following the exceptionally destructive 2005 hurricane season. A small study of risk perception and optimistic bias was conducted immediately following Hurricanes Katrina and Rita. Two years later, a follow-up was done in which respondents were recontacted. This provided an opportunity to examine changes, and potential causal ordering, in risk perception and optimistic bias. The analysis uses 201 panel respondents who were matched across the two mail surveys. Measures included hurricane risk perception, optimistic bias for hurricane evacuation, past hurricane experience, and a small set of demographic variables (age, sex, income, and education). Paired *t*-tests were used to compare scores across time. Hurricane risk perception declined and optimistic bias increased. Cross-lagged correlations were used to test the potential causal ordering between risk perception and optimistic bias, with a weak effect suggesting the former affects the latter. Additional cross-lagged analysis using structural equation modeling was used to look more closely at the components of optimistic bias (risk to self vs. risk to others). A significant and stronger potentially causal effect from risk perception to optimistic bias was found. Analysis of the experience and demographic variables' effects on risk perception and optimistic bias, and their change, provided mixed results. The lessening of risk perception and increase in optimistic bias over the period of quiescence suggest that risk communicators and emergency managers should direct attention toward reversing these trends to increase disaster preparedness.

**KEY WORDS:** Demographics; Gulf Coast; hurricanes; optimistic bias; risk perception

## 1. INTRODUCTION

This study focuses on levels of concern for hurricanes among individuals living along the Gulf Coast during the quiescent two-year period following the exceptionally destructive 2005 hurricane season. We had concluded a small study of risk perception and optimistic bias immediately following Hurricanes Katrina and Rita.(1) Two years later resources were marshaled to conduct a modest *ad hoc* follow-up, in which we recontacted the same individuals who responded to the first study. This provided an opportunity to examine changes, and potential causal ordering, in risk perception and optimistic bias.

A great deal of research has been published on both risk perception and on optimistic bias. And as reviewed below, a fair amount resides in the domain of natural hazards, as well as hurricanes specifically. But, to our knowledge, no study has been published in which longitudinal panel data have been employed

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to look at the temporal relationship between risk perception and optimistic bias. This study offers some insight into that question.

Why would we expect there to be changes in risk perception and optimistic bias for hurricanes, and why would this be important? These questions are central to the motivation to conduct this follow-up study. It has been shown that the concerns people hold about a hazard can diminish over time given the absence of an obvious or recent manifestation of the hazard. For example, Valdiserri describes how concern over the threat of HIV/AIDS has decreased as improved use of preventative measures and more effective treatments have become more common.(2) This phenomenon also occurs at organizational and institutional levels. In the context of industrial accidents, Freudenburg described this phenomenon as the "atrophy of vigilance."(3) Such diminishing levels of risk concern have been identified in the realm of natural disasters as well—often in the parlance of a false-alarm or "cry wolf" effect in terms of warnings, but also with respect to prolonged periods of quiescence.(4–6)

Hurricane forecasters raised this concern last year in light of a six-year period that the United States went without a category 3+ hurricane landfall (the longest stretch in government records since 1851, so far spanning the 2006–2012 seasons). An August 2012 feature story in *USA Today* put it this way: "As the USA nears 2,500 days without a Category 3 or higher hurricane, weather and disaster experts worry that Hurricanes Wilma, Katrina, and Rita will become hazy memories and Americans will go soft, letting their batteries die, misplacing their flashlights, and forgetting their emergency plans. . . . 'It's easy to become complacent, but we have to snap ourselves out of it,' says Rick Knabb, director of the National Hurricane Center."(7)

Insight into the process by which complacency may develop is an important concern for those who must plan for and promote individual-level preparedness for hurricanes. It is also an important factor for community and regional preparedness for evacuations. To frame our study we will first discuss relevant previous work addressing risk perception and optimistic bias and their change over time. We will also provide a basis for the examination of a small set of demographic variables as potential explanatory mechanisms for such changes.

## 2. BACKGROUND

Although the literature on risk perception has grown to a very substantial volume, relatively limited attention has been dedicated to risk perception in the context of natural hazards. Studies examining risk perception for flooding, volcanoes, and earthquakes, for example, have shown risk perception or hazard concern to be associated with information seeking and various aspects of disaster preparedness.(8–11) Risk perception for hurricanes resides in this area of literature and has been identified as a research priority.(12) Results in the available hurricane literature also indicate that risk perception is associated with disaster preparedness, as well as with evacuation behavior.(13–18)

One study on hurricane risk perception is especially relevant to the work we present here. In a phone survey of single-family homeowners in Florida, Peacock *et al.* looked at the relationship between hurricane risk perception and experiential (years as a Florida resident, hurricane experiences), sociodemographic (gender, age, income, race, education, and children in household), and spatial factors (home location in wind hazard zones).(12) They reported that all variables were significant predictors of hurricane risk perception except children in the home, hurricane experience, and hurricane knowledge. The three-item measure they used for hurricane risk perception was the best previously used measure at the time of the work we report here. It is described below.

Turning to change in risk perception, a number of studies have found associations between time variables such as length of residence and perception of natural hazards risk. It has been observed for some time that newer coastal residents tend to be more likely to evacuate from hurricanes, for example, or that length of residence in an earthquake zone is associated with lower perception of earthquake risk (see Lindell(19) and Cross,(20) respectively, for reviews of earthquakes and hurricanes).

But few studies have used longitudinal methods to look at change in hurricane risk perception, and have done so with differing results. Cross conducted a survey of lower Florida Keys residents over a 12-year period, recontacting the same individuals at three points (1978, 1982, 1988).(20) He found good stability of concern for hurricane risk even as the area went without a major landfall for his study period, and had not had a major landfall in the previous 20 years. More recently, Baker *et al.* conducted a longitudinal study of individuals displaced by Hurricanes Katrina and Rita, assessing their view of the likelihood of New Orleans being again struck by a major hurricane. They interviewed study participants shortly after the disasters and then again a year later (also adding a second sample). They did find a modest fading of risk perception.[21,22]

As with risk perception, optimistic bias has received substantial attention. Also known as comparative optimism, optimistic bias is the circumstance in which individuals believe themselves to be less likely harmed by negative events as compared to others or, conversely, that they will be more likely than others to achieve some goal or status.[23,24] Optimistic bias manifests in a wide range of circumstances.[25] It has been shown to be stable over time. Sheppard examined the stability of optimistic bias across different risk targets and their consistency within risk targets across time, in this case using a set of common negative life events (weight gain, depression, cancer, etc.).[26] It was shown that there is inconsistency across risk targets, but temporal consistency in optimistic bias within specific risks, at least absent an intervening life experience.

Relatively little work has examined optimistic bias concerning natural hazards. Our previous study appears to still be the only work on optimistic bias with hurricanes, in which it was found that being older, having lived on the coast longer, and being more optimistic in general were all positively associated with optimistic bias to hurricane risk.[1] There is also some available literature on earthquakes, in which stability over time has been examined as well. Burger found a lack of optimistic bias for earthquakes in months immediately following the disaster, with those individuals who experienced more significant losses being the least likely to display such bias. But optimistic bias was seen to emerge several months later.[24] In another study of individuals exposed to an earthquake, subjects' consistency in optimistic bias across time was also assessed. Those having greater levels of loss with the earthquake showed less optimistic bias. This study also followed participants and found no emergence of optimistic bias at five months.[27] In a reanalysis of that study along with new data, Shepperd concluded that intervening experience moderates optimistic bias, causing it to destabilize for a period of time before returning.[26]

Another key question that may be addressed in a longitudinal design is the causal relationship between risk perception and optimistic bias. Greater levels of risk perception are associated with lower levels of optimistic bias, with a host of factors potentially influencing this association.[28] But does the perception of risk constitute an initial condition necessary for the formation of optimistic bias? Or are they cotemporaneous, or does bias influence risk perception? No studies were found that directly assessed this question, which is explored herein. This question might also be expanded to uniquely examine the two components of optimistic bias: perception of risk for self and for others. There has been work looking at various influences on these two components,[25,29] but none on how they might uniquely be related to risk perception over time.

Finally, our initial data collection provided a small set of demographic variables that have been previously examined in relation to risk perception and optimistic bias. We briefly examine age, sex, education, income, and past hazard experience.

Research on how age is associated with optimistic bias in health research has shown an effect but not a directionally consistent one. Younger persons are more biased about heart disease, older smokers more biased about lung cancer, and younger persons more biased about food poisoning.[30–32] Age was not found to be a significant predictor of having an optimistic bias when it came to being a victim of a domestic abuse crime.[33] The findings with respect to age and risk perception are similar: age does matter but its role varies by context.[34,35]

Many studies show that men tend to perceive less risk than do women.[36] But like age, the literature detailing how sex covaries with optimistic bias has been inconsistent and, again, contextually dependent. A study focused on sun protection in young adults living in Australia found that females rated skin cancer as more severe than males did.[37] Other researchers have reported that men demonstrate greater levels of optimistic bias regarding their driving skills than women do, and also rate actions such as driving without a seat belt or not making a full stop at a stop sign as less serious than women do.[38] But other studies in the domain of health (the overweight among college students, diabetes among physicians) have found no significant differences by sex.[39,40]

In a recent article, Peterson *et al.* acknowledge the lack of work on income and education and optimistic bias. Their study on patients with hypertension found a significant effect from education (more education, more bias) but only equivocal findings from income.[41] Income was found to be a predictor of the related phenomenon of unrealistic optimism.[42] Three other recent studies involving health risks all found a positive association between educational attainment and optimistic bias: higher levels of educational attainment predicted greater optimistic bias for heart attack risk,[43] bias for breast cancer,[44] and lower risk perception and greater bias concerning acute gastrointestinal illness.[45]

A number of studies on optimistic bias have included the effect of past experience, with mixed results depending on whether studies targeted positive or negative events and the context of experience. Optimistic bias has been observed to increase with personal experience for negative outcomes.[46] In the context of experience gained through training, greater levels of hazardous activity training (firefighting, military, and skydiving) increases optimistic bias.[47] Conversely, the majority of studies have found (e.g., for health problems, online privacy, computer viruses, salmonella, and automobile accidents) that greater levels of personal experience with the risk leads to lower levels of optimistic bias—or even that optimistic bias is entirely eliminated in the case of a significant negative experience (i.e., an earthquake).[48–52] A meta-review has shown that this effect is activated by personal experience moderating the level of individual optimism.[25]

With respect to risk perception and natural hazards, Halpern-Felsher found that at least among adolescents, previous experience tended to lower perceptions of future risk.[53] Work specifically addressing past experience with hurricanes has shown that those with greater levels of experience tend to have greater levels of risk perception, greater levels of preparedness, and greater tendency to evacuate.[54–56] In both cases (risk and bias), and more broadly in the disasters literature, past experience has been identified as an important concept.[57–59] While a deceptively complicated concept, within the present context, its mechanism of effect can be viewed within the frame of availability.[60–62] The degree to which individuals can recall from memory any aspect of a hurricane experience will enhance their perception of its importance.

In summary, previous work supports the contention that over the course of two years without a major hurricane threat individuals will exhibit greater optimistic bias and lower levels of risk perception for hurricane risk in the upcoming season. The causal relationship between risk perception and optimistic bias has not been examined in longitudinal data, so the direction of this relationship is not predictable. Similarly, the directional relationships between risk perception and the two elements of optimistic bias have not been examined. And taken together, the previous work on demographics relevant to this investigation offers fairly equivocal guidance concerning the direction of anticipated relationships. This argues for the investigation of three hypotheses and four research questions.

H1: = *Respondents will perceive less risk from hurricanes in 2008 versus 2006.*
H2: = *Respondents will express greater optimistic bias for hurricanes in 2008 versus 2006.*
H3: = *The self and other components of optimistic bias will increase from 2006 to 2008.*
$RQ_1$: = *Is there a directional relationship between risk perception and optimistic bias?*
$RQ_2$: = *Is there a directional relationship between risk perception and the components of optimistic bias?*
$RQ_3$: = *Which of the demographic variables predict risk perception and optimistic bias?*
$RQ_4$: = *Which of the demographic variables predict change in risk perception and optimistic bias?*

## 3. METHODS

### 3.1. Data Collection

Data collection was accomplished through a mail survey sent to households living in 41 counties immediately adjacent to the Gulf Coast. This sample area extends from Naples, Florida to Brownsville, Texas, with the exclusion of the area from the west side of Mobile Bay, Alabama to Galveston, Texas. The sample excluded the area of destruction from Hurricanes Katrina and Rita due to the ongoing disruption in this region. It is worth noting that Hurricane Ivan made landfall near the Florida-Alabama border the previous season. The Atlantic coast was not included in the design for two reasons: the additional cost would have been prohibitive relative to the likely gain in findings and, second, the symmetry of the Gulf Coast provides a more unified meteorological and geographic domain in which to observe proximity. The sample area, based on counties, averaged 70 miles inland. This strip of land is home to approximately 7 million people, with an average of 300 persons per square mile.

The University of Wisconsin Survey Center was employed to execute the survey using best-response methods that included an advance phone call, a $5 incentive, and appropriate follow-up mailings. A stratified sample of 1,375 households was drawn by Survey Sampling International in which 41 coastal counties were first specified. Within each county between two and five zip codes were randomly selected, yielding a total of 141 zip codes.

Within each zip code, between eight and 20 households were randomly selected, the number depending on the number of zip codes per county (some counties had only two through four zip codes). The goal was to select at least 30 households per county. An average of 34 households were selected per county, with an average of 10 per zip code. The stratified sample design was employed in order to improve the spatial distribution of cases within counties. Simple random samples of county areas with embedded population centers tend not to be spatially random, but rather weighted toward the population centers. Instructions on the questionnaire indicated that any adult member of the household could complete the questionnaire.

The survey was initiated on January 12, 2006 and returns were collected through March 17, 2006. A total of 843 questionnaires were returned. Using American Association for Public Opinion Research criteria, the response rate was calculated as completed returns divided by sample points minus nonsample cases.[63] Only seven nonsample cases were identified (deceased or noneligible adult respondent), yielding a response rate of 61.5%. Of the 843 completed returns, nine were subsequently eliminated because they had the tracking code removed (defeating geocoding) and 10 were eliminated because they fell outside of the defined study area (sampling errors). A final total of 824 cases were available for analysis (60% response).

Data collection to facilitate the second wave survey was executed two years later, in January 2008. An identical questionnaire was sent to the 824 completions from 2006. The mailing was done from the investigators' campus, and no incentive payments were used. From the first mailing, 128 addresses came back as undeliverable. This provides an estimate of 16% for two-year attrition from relocation. The second data collection yielded a 52% adjusted response rate to establish the panel data set of 361 cases.

Instructions on the questionnaire indicated that the same individual who completed the previous survey should complete the second one. A question was included to ask if the respondent recalled completing the previous survey: 73% indicated yes. We then examined the data for match on sex and age, identifying 201 cases (56%). Within this segment 87% reported recall of the previous survey. We decided to limit our analysis to these 201 cases. This involves a tradeoff between representativeness and the necessary consistency for individual-level panel data. We chose the latter.

### 3.2. Measures

A set of three questions taken from Peacock *et al.*[12] form a scale of *hurricane risk perception*, each with a five-point response running from "very unlikely" to "very likely" and coded such that higher values represent less risk perception (or greater optimism): How likely do you think it is that a hurricane will prevent you or members of your household from being able to go to work or go to your jobs during the next hurricane season? How likely do you think it is that a hurricane will disrupt your daily activities during the next hurricane season? and How likely do you think it is that a major hurricane will potentially damage your home during the next hurricane season? The items form an additive scale with good reliability by Cronbach's test ($T_1$ $\alpha = 0.82$, $T_2$ $\alpha = 0.81$).

A second dependent variable was created for *optimistic bias*. Alternate approaches for measuring optimistic bias have been used: the difference score and the use of a direct measure asking subjects to state their risk as compared to others (lesser, same, and greater). But in the latter approach it has been found that the estimate of risk for average others is made based on the estimate of risk for self and recommendations have been made to discard the direct approach in favor of the difference score.[29]

At separate places in the questionnaire, two items asked for respondents' estimation of the probability of a forced evacuation for others living on the Gulf Coast and for themselves in the following hurricane season, with a response scale of 0–100% in 5% increments (again, for consistency, with risk perception coded such that high values indicate more optimistic outlook). The items were: For the average individual living on the Gulf Coast, what would you say the chances are (from 0% to 100%) that he or she will be forced to evacuate from a major hurricane during the next hurricane season? and What would you say the chances are (from 0% to 100%) that you will be forced to evacuate from a major hurricane during the next hurricane season? Forced evacuation could be the consequence of an emergency order or a personal safety decision to leave. In either case it would reference a significant event. The variables are labeled here as "Self" and "Others" for $T_1$ and $T_2$. To compute the difference score between self and others a simple bivariate regression was employed to create a residual score. These variables are labeled Bias $T_1$ and Bias $T_2$.

Change (or gain) variables were then calculated for both risk perception and optimistic bias. Controversy has plagued the use of gain scores in analyses of change, at least since a 1970 paper by Cronbach and Furby.(64) Many studies have used a simple arithmetic approach to compute change from identical pretest and posttest measures (i.e., subtracting pre from post). Various issues are raised by this approach, including base-rate control and regression to the mean (indicated when pretest and posttest scores are negatively correlated).(65) Various researchers have advocated alternate approaches such as residualized gain scores, first-order differencing, regression modeling, polynomial regression with surface analyses, and structural equation modeling.(65–70) Nonetheless it is still common to find analyses of change over time using gain scores calculated arithmetically.(71) As we observed no negative associations across time we elected to use this simplest approach. These variables are labeled ΔRisk and ΔBias.

The survey included demographic items for sex (female = 0, male = 1), age (date minus year of birth as reported on the survey), annual household income (1 = less than \$10,000 through 9 = greater than \$80,000), and educational attainment (1 = less than high school through 7 = doctorate, medical, law, or similar). Income and education were only measured in 2006 as significant changes were not anticipated. Sex and age were measured at both times to be used to match cases.

Hurricane experience was measured using a set of three items to indicate overall experience with three degrees of hurricane impact: How many hurricanes have you been in? How many times have you evacuated from a hurricane? How many times have you had property damage from a hurricane? This was also measured only in 2006. The resulting additive index has a reliability of $\alpha = 0.51$. To correct the negatively skewed distribution toward normal, a square root transformation was applied.

## 4. RESULTS

Analyses were done using SPSS (v. 21). Descriptive statistics are reported in Table I. The sample was 65% male with an average age of 62 years (range from 20 to 92 and approximately normal). The mean level of educational attainment of 3.5 corresponds to some college or technical school, although 15% of

**Table I.** Correlations (Above), Covariances (Below), with Means and (Standard Deviations) on the Diagonal

| | Risk T1 | Risk T2 | Bias T1 | Bias T2 | ΔRisk | ΔBias | Others T1 | Self T1 | Others T2 | Seld T2 | Age | Male | Income | Education | Experience |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk T1 | 8.52 (2.90) | 0.45** | −0.37** | −0.12*** | −0.57** | 0.18** | −0.65** | −0.57** | −0.39** | −0.40** | −0.23** | −0.12 | −0.17* | −0.06 | 0.30** |
| Risk T2 | 3.514 | 9.83 (2.69) | −0.10 | −0.28* | 0.47** | −0.14*** | −0.31** | −0.35** | −0.72** | −0.71** | −0.24** | −0.19** | −0.03 | −0.04 | 0.18** |
| Bias T1 | −1.07 | −0.28 | 0 (1) | 0.12 | 0.27** | 0.62** | 0.77** | 0.00 | 0.20** | 0.17* | 0.15* | 0.08 | −0.01 | 0.05 | −0.14* |
| Bias T2 | −0.36 | −0.76 | 0.11 | 0 (1) | −0.14 | −0.67** | 0.16* | 0.11 | 0.63** | 0.00 | 0.22** | 0.01 | −0.05 | 0.03 | 0.04 |
| Δ Risk | −0.49 | 3.7 | 7.7 | −27.9 | 1.31 (2.94) | −0.31** | 0.36** | 0.24** | −0.28** | −0.24** | 0.01 | −0.05 | 0.15* | −0.01 | −0.13 |
| Δ Bias | 0.7 | −0.5 | 19.2 | −13.7 | 1.19 | 0.0(1.33) | −0.46** | 0.8 | 0.32** | −0.13*** | 0.05 | −0.06 | −0.03 | −0.02 | 0.14* |
| Others T1 | −49.9 | −21.9 | 20.3 | 4.1 | −27.9 | −16.1 | 50.52(26.46) | 0.64** | 0.40** | 0.39** | 0.21** | 0.19** | 0.11 | 0.10 | −0.25** |
| Self T1 | −48.0 | −27.8 | 0.00 | 3.06 | −20.3 | 3.1 | 490.9 | 55.24(28.94) | 0.39** | 0.41** | 0.14* | 0.19** | 0.19** | 0.08 | −0.22** |
| Others T2 | −26.5 | −45.1 | 4.7 | −14.5 | 18.6 | 9.9 | 246.2 | 258.15 | 60.39 (23.04) | 0.77** | 0.31** | 0.15* | 0.05 | 0.13 | −0.13 |
| Self T2 | −27.4 | −43.4 | 3.9 | 0.00 | 16.4 | −3.8 | 239.9 | 275.2 | 411.1 | 67.55 (23.02) | 0.23** | 0.18** | 0.11 | 0.15* | −0.21** |
| Age | −9.4 | −8.9 | 2.1 | 3.0 | −0.05 | 0.9 | 75.7 | 57.2 | 100.1 | 72.4 | 62.32 (13.89) | 0.02 | −0.19** | −0.01 | −0.12 |
| Male | −0.2 | −0.2 | 0.04 | −0.01 | 0.7 | −0.04 | 2.4 | 2.7 | 1.6 | 2.0 | 0.11 | 0.65 (0.48) | 0.21** | 0.06 | −0.06 |
| Income | −1.2 | −0.18 | −0.03 | −0.11 | −0.9 | −0.1 | 6.8 | 12.5 | 2.9 | 5.9 | −6.2 | 0.23 | 5.37 (2.29) | 0.38** | −0.02 |
| Education | −0.25 | −0.19 | 0.09 | −0.05 | −0.1 | −0.1 | 4.2 | 4.1 | 4.9 | 5.5 | −0.22 | 0.05 | 1.4 | 3.46 (1.58) | 0.05 |
| Experience | 4.4 | 2.5 | −0.69 | 0.22 | 1.9 | 0.9 | −32.6 | −31.6 | −15.5 | −24.1 | −8.9 | −0.16 | −0.32 | 0.39 | 7.43 (4.99) |

*Note:* $N = 201$. Coefficients above the diagonal involving nominal by interval associations report ETA, nominal by nominal report PHI, all others report Pearson.
*$p < 0.05$, **$p < 0.01$, ***$p < 0.10$.

the sample reported completing a college degree and 14% reported completing a graduate or professional degree. The average annual household income of 5.4 corresponds to the \$40,000–\$49,000 bin, with a normal distribution aside from a secondary mode in the highest bin (15% reporting greater that \$80,000). On average, respondents report a 7 on the hurricane experience scale, which ranges from 0 to 30. The component asking about the number of hurricanes experiences has an average of 4.6 and a range from 0 to 10.

Paired t-tests were used to test hypotheses H1–H3. The change in risk perception was significant, indicating a more optimistic outlook (mean difference 1.31, $t_{(200)} = 6.3$, $p < 0.001$). The first hypothesis is confirmed: respondents did perceive less risk from hurricanes in 2008 when compared to 2006. The change in optimistic bias was not significant (mean difference 2.43, $t_{(200)} = 1.3$, $p = 0.21$). The second hypothesis is not supported. However, both components of optimistic bias did change significantly. The estimated probably for others having to evacuate became more optimistic (mean difference 9.87, $t_{(200)} = 5.2$, $p < 0.001$), as did the estimated probability for self (mean difference 12.30, $t_{(200)} = 6.1$, $p < 0.001$). Hypothesis H3 is supported.

The first research question asks if there a directional relationship between risk perception and optimistic bias. To assess this we examine the correlations in Table I to consider the cross-lagged relationship between risk perception and optimistic bias. The correlation between risk perception at time 1 and optimistic bias at time 2 is significant, but only at the relaxed alpha level of 0.10. The correlation between optimistic bias at time 1 and risk perception at time 2 is not significant. The difference between the two correlations is not significant. These results suggest a weak directional effect in which risk perception precedes optimistic bias.

The second research question seeks to unpackage the components of optimistic bias, self and others. Again, a cross-lagged correlation approach was used. Looking at the correlations in Table I, we see that the correlation between risk perception at time 1 and others at time 2 is 0.39 and significant, while the correlation between others at time 1 and risk perception at time 2 is 0.31 and also significant. We also see that the correlation between risk perception at time 1 and self at time 2 is 0.40 and significant, while the correlation between self at time 1 and risk perception at time 2 is 0.35 and also significant.

To further examine these associations, and test differences across coefficients, we next used AMOS (v. 21) to evaluate a path model such that all of the relationships in the set of cross-lagged correlations could be assessed simultaneously and differences in coefficients could be tested. These results are shown in Fig. 1. With temporal autocorrelations and within-time correlations controlled a less equivocal result is seen. Here the directional effects are consistent and significant from risk perception at time 1 to the components of optimistic bias at time 2. Paths from self and others at time 1 to risk at time 2 are not significant. Also the two conceptually paired differences among these paths are also significant (–0.35 and –0.10 for self; –0.31 and –0.06 for others; both $p < 0.01$). While the model is measured with error, the fit statistics are close but not strong ($n = 201$, $\chi^2_{\mathrm{df}=2} = 7.9$, $p = 0.012$, RMSEA $= 0.12$, $p$-close $=$ 0.07, CFI $= 0.99$).

To assess the third and fourth research questions a set of multiple regressions were done. These are reported in Table II. Age and past hurricane experience are consistent predictors of risk perception at both time points, with older individuals and those with more hurricane experience having lesser risk perceptions (again, higher values). Age and experience are not themselves correlated. Income is only significant at time 1, and sex only significant at time 2. If these effects differ at higher and lower levels of risk then it would indicate that higher levels of income become less predictive of lower levels of risk as the risk increases (perhaps a "protective factor" with a ceiling effect), and the different in risk perception between men and women only manifests at higher levels of risk.

Optimistic bias was not as well predicted by this set of demographic variables. The only semi-consistent predictor at both time points is age, and then only with a relaxed alpha at time 1. At time 2 older individuals exhibit a greater optimistic bias. If the change on age from time 1 to time 2 is accepted it may suggest that this effect does not appear at lower levels of optimistic bias, a floor effect.

Finally, the change variables are each only predicted by one of the demographic variables. Since the average value of risk perception increased (indicating less risk) and higher values on the change variable indicate greater movement to higher levels the inverse association with income indicates that those at lower income levels were most likely to become more positive in their risk assessments.

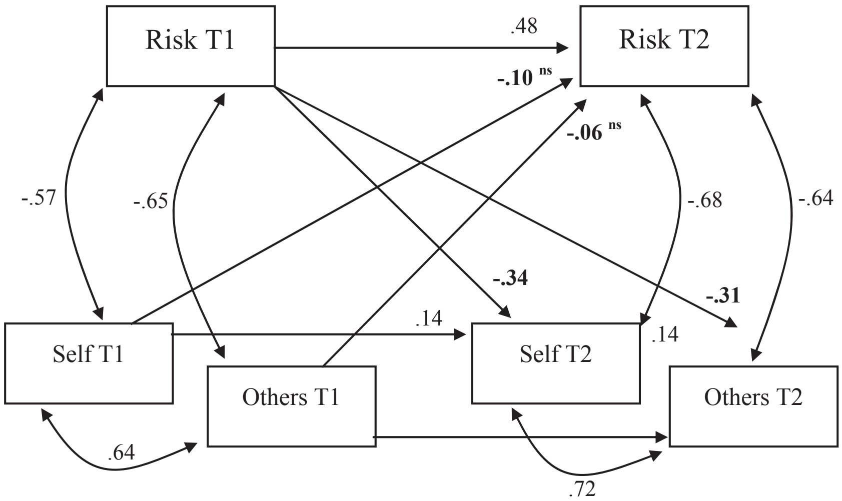


**Fig. 1.** Confirmatory structural model of cross-lagged effects between risk and bias elements. All standardized coefficients significant $p < 0.05$ unless indicated (ns). Lagged coefficients in boldface. Model fit: $n = 201$, $\chi^2_{\mathrm{df}=2} = 7.9$, $p = 0.012$, RMSEA = 0.12, $p$-close = 0.07, CFI = 0.99.

**Table II.** Regression Models Predicting Risk Perception, Optimistic Bias, and Their Change ($N = 201$)

| DV/IVs | $\beta$ | $t_{(195)}$ | $p$ | $_{\mathrm{adj}}R^2$ | $F_{(5,\,195)}$ | $p$ | DV/IVs | $\beta$ | $t_{(195)}$ | $p$ | $_{\mathrm{adj}}R^2$ | $F_{(5,\,195)}$ | $p$ |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Risk T1 | | | | 0.16 | 8.4 | <0.01 | Bias T1 | | | | 0.02 | 1.9 | 0.095 |
| Sex (male) | −0.06 | −0.9 | 0.37 | | | | Sex (male) | 0.08 | 1.0 | 0.29 | | | |
| Age | −0.24 | −3.6 | <0.01 | | | | Age | 0.13 | 1.8 | 0.08 | | | |
| Income | −0.21 | −2.8 | <0.01 | | | | Income | −0.03 | −0.4 | 0.68 | | | |
| Education | 0.01 | 0.2 | 0.86 | | | | Education | 0.07 | 0.9 | 0.34 | | | |
| Experience | 0.26 | 3.9 | <0.01 | | | | Experience | −0.12 | −1.7 | 0.09 | | | |
| Risk T2 | | | | 0.09 | 5.1 | <0.01 | Bias T2 | | | | 0.03 | 2.2 | 0.056 |
| Sex (male) | −0.17 | −2.5 | <0.05 | | | | Sex (male) | 0.01 | 0.1 | 0.90 | | | |
| Age | −0.22 | −3.2 | <0.01 | | | | Age | 0.22 | 3.1 | <0.01 | | | |
| Income | −0.02 | −0.3 | 0.79 | | | | Income | −0.02 | −0.2 | 0.81 | | | |
| Education | −0.04 | −0.5 | 0.62 | | | | Education | 0.04 | 0.05 | 0.64 | | | |
| Experience | 0.15 | 2.2 | <0.05 | | | | Experience | 0.07 | 1.0 | 0.32 | | | |
| ΔRisk | | | | 0.02 | 1.9 | 0.09 | ΔBias | | | | 0.01 | 1.1 | 0.38 |
| Sex (male) | −0.09 | −1.4 | 0.18 | | | | Sex (male) | −0.05 | 0.49 | | | | |
| Age | 0.03 | 0.5 | 0.63 | | | | Age | 0.07 | 0.33 | | | | |
| Income | 0.19 | 2.4 | <0.05 | | | | Income | 0.01 | 0.89 | | | | |
| Education | −0.05 | −0.6 | 0.55 | | | | Education | −0.03 | 0.72 | | | | |
| Experience | −0.12 | −1.7 | 0.09 | | | | Experience | 0.15 | <0.05 | | | | |

For change in optimistic bias, the same directional interpretation applies. So the positive association with hurricane experience indicates that those with the greatest levels of past experience were most likely to becomes more optimistically biased.

## 5. DISCUSSION

While aspects of this study impose important limitations (discussed below), several of the findings nonetheless offer unique contributions to the expansive literatures on risk perception and optimistic bias, and suggest potentially interesting avenues for further investigation. Other results support previous findings.

First, the change in risk perception is consistent with previous studies looking at natural disasters more generally (e.g., earthquakes), consistent with the more recent work on hurricanes by Baker *et al.*, and consistent with the anecdotal expectations discussed in Section 1. The lessening of risk perception for hurricanes over a quiet two-year period following a highly destructive season implies a relaxing of concern in the absence of an immediate threat. This shift was reasonably strong as well. For the

$t$-value of 6.3 with 200 $df$ Cohen's $d = 0.89$ and $r = 0.41$, both approaching or within bounds considered to be strong effects.[72] Given that this shift was observed in a panel design and is well outside of the bounds of random effect, this finding offers an important observation that may inform future studies of changes in hazards risk perception.

The findings on change in optimistic bias are directionally similar to risk perception albeit not as strong. This is also consistent with some past studies of optimistic bias. The studies reviewed above by Burger and by Sheppard showed optimistic bias returning slowly. Given that hurricane season is an annual phenomenon two years may have not yet provided sufficient reinforcement for optimistic bias, which was shown in other studies (especially those in a health context) to be relatively stable.

Interestingly, the directional changes in the components of optimistic bias were significant and strong (similar effect sizes as for risk perception). This seems to point to a challenge in using difference scores longitudinally. As the computation of optimistic bias at both time points inevitably yields a distribution around a mean that is close to zero a significant $t$-test would require a concomitant narrow distribution and/or a larger $N$. The computation makes the effect more difficult to detect, and the analysis embodies difficulties from both difference and gain scores. Alternately, change in optimistic bias might be best assessed using the direct measurement approach, despite the problems that have been identified there. Optimally, attention may be turned toward development of a better measurement approach for optimistic bias, especially for use in longitudinal work.

The finding on the longitudinal effect between risk perception and optimistic bias is the most unique contribution of this study. The simple cross-lagged correlations between the four computed variables provide only marginal support for the finding that risk perception affects optimistic bias. But with the unpackaging of the components of optimistic bias the effect is more pronounced. This, of course, seems to also be a difficulty flowing from the manner of calculating optimistic bias in that the mean of the difference variable inherently draws toward zero. No previous work was found to suggest this directionality of effect. But one might consider that risk perception should precede optimistic bias as it is necessary to form that judgment before it is possible to evaluate how it might differentially apply to self versus other. This finding clearly suggests an avenue for further investigation.

The results with the demographic variables are mixed but offer some useful insight. The effect of past experience reducing risk perception is not consistent with the previous studies on hurricanes. It is possible that those in this sample with greater levels of experience are also among those most prepared, although preparedness was not assessed. This may hold as well with the effect of experience on change in optimistic bias. At first glance one might suspect that the effect of age on risk perception is associated with experience, but the two are not correlated. Coastal areas are popular for retirement, so people may move there in their later years with little or no hurricane experience. Thus the association of greater age and lower risk perception may be a more general phenomenon, as has been seen in some previous studies. That age is also a significant predictor of optimistic bias (provisionally at time 1) may underscore this possibility.

Probably the most intriguing finding with the demographic variables is that described above for income and risk perception. To further underscore the possibility that propensity to change in risk perception may be conditioned on income level we split income at the mean and ran a $t$-test on change in risk perception. The mean change value for the low income group (1.76) was significantly higher than for the high income group (0.72) ($t = 2.5$, $df = 199$, $p < 0.05$). So only those in the lower levels of income became markedly more positive toward hurricane risk. Given the many factors that are associated with income, it is difficult to speculate on a mechanism for this. But given the higher levels of vulnerability often associated with lower income, this may merit further investigation.

These findings, of course, must be considered in light of the several limitations of this study. This follow-up investigation was not planned at the time of the first study, so the inclusion of variables that might have been more robust in predicting change was not considered. The use of a more purposive tracking mechanism to link individual responses was also not optimal for this reason. Although the matching used here is held to be strong, it ended up reducing sample size and potentially affecting the representativeness of the data in ways that cannot be directly assessed here.

Measurement of risk perception is not optimal. Current theory and a good body of work supports an approach to employ a dual-process model of risk perception to assess cognitive and affective factors uniquely. We had a preference for a previously used measure specific to hurricanes at the time as the first project was a rapid response in the wake of Hurricane Katrina. Developing our own measure at the time was infeasible.

Measurement challenges with optimistic bias were discussed above, and this poses a more general problem that deserves future attention. With respect to optimistic bias as a concept in this study, a unique issue is that the focus of the risk target for the optimistic bias measures differs from that of the risk perception measure, a more controllable damage or harm outlook versus a less controllable forced evacuation. Nonetheless, the measure of optimistic bias is relevant to hurricane outlook, and the two measures are significantly correlated within the two time periods.

Some debate has been presented recently concerning optimistic bias being more of a statistical artifact than an actual phenomenon. Harris and Hahn offer such a criticism and identify scale attenuation (e.g., using a 1–7 level response for a continuous phenomenon), minority undersampling (absence of classes of individual more likely to suffer from the hazard, e.g., a disease), and base rate regression (individual over- and underestimation of actual rates with error tending toward the mean).[73] They also point out that these issues are exacerbated when dealing with relatively rare occurrences (e.g., lung cancer).

On the first two points, this study is not strongly affected. We used a response scale allowing for 5% increments so scale attenuation is less of a problem. Since we were investigating a natural hazard that occurs on geographic scales and sampled within such a scale, no high-risk subpopulations were excluded. We are also investigating a hazard that is not especially rare. In terms of base rate regression, we agree with the more recent view on the matter that has been offered by Shepperd *et al.* In a response to Harris and Hahn they argue that base rate regression should not be seen as an artifact: "Rather, it should be viewed merely as one of many explanations for the finding that people can believe that they are at lower risk than their peers."[74 p. 401]

The final analysis using structural modeling is essentially a path analysis because no latent measures were used. This approach does have the advantage of offering an assessment of overall model fit. The fit indices for this analysis are marginal, or as is typically said "close." Given that the set of correlations are fairly strong, an important contributor to the models marginal degree of fit likely resides in the measures used.

Finally, the design of this study does not support a formal argument for causality. While the cross-lagged analysis indicates a time-forward association between risk perception and optimistic bias, and not vice versa, it is not possible to eliminate the possible effects of other plausibly important unobserved variables. We do believe, however, that this finding is sufficient to motivate further investigation into the possible casual association.

Turning to implications for practice, two findings from this study might inform efforts in the domains of risk communication and emergency planning. First, if greater levels of past experience reduce risk perception and optimistic bias this might add credence to the concerns expressed in Section 1 regarding complacency. If concern falls over a quiescent period even among those with greater experience more attention may be need for reinforcing messages and preparedness campaigns. If those with less experience have greater levels of concern then this may also offer an avenue for promotion of preparedness, perhaps especially among newly arrived retirees.

Second, this study demonstrates clearly that, over time, levels of risk perception for hurricanes can change—even in the aftermath of a devastating hurricane season. While the design of this study does not support a strong causal conclusion that it is quiescence that leads to lessening risk perception, it is a plausible argument. This study did not assess any elements of preparedness, so the proposition on complacency is indirect. Nonetheless, this finding could certainly be used to support the need for enhanced preparedness messages and other efforts as areas go for longer periods without a hurricane. Furthermore, even when areas have been struck by major disasters, emergency planners should not assume that complacency will not set in soon (i.e., within a one- to three-year time span) after the event.

## ACKNOWLEDGMENTS

This work was supported by the National Science Foundation Small Grants for Exploratory Research program (SES-055492) and a mini-grant from the Center for Research on Communication & Technologies at Colorado State University.

## REFERENCES


1. Trumbo C, Lueck M, Marlatt H, Peek L. The effect of proximity to Hurricanes Katrina and Rita on subsequent hurricane outlook and optimistic bias. Risk Analysis, 2011; 31(12):1907–1916.
2. Valdiserri RO. Mapping the roots of HIV/AIDS complacency: Implications for program and policy development. AIDS Education & Prevention, 2004; 16(5):426–439.
3. Freudenberg WR. Nothing recedes like success? Risk analysis and the organizational amplification of risks. Risk: Issues in Health and Safety, 1992; 3(1):1–35.
4. Atwood L, Major A. Exploring the "cry wolf" hypothesis. International Journal of Mass Emergencies and Disasters, 1998; 16(3):279–302.
5. Wang X, Kapucu N. Public complacency under repeated emergency threats: Some empirical evidence. Journal of Public Administration Research & Theory, 2008; 18(1):57–78.
6. Simmons K, Sutter D. False alarms, tornado warnings, and tornado casualties. Weather, Climate, and Society, 2009; 1:38–53.
7. Leger D. Hurricane warning: Is USA becoming complacent? USA Today, August 21, 2012.
8. Mileti D, Darlington J. The role of searching in shaping reactions to earthquake risk information. Social Problems, 1997; 44:89–103.
9. Perry R, Lindell M, Greene M. Threat perceptions in public response to volcano hazard. Journal of Social Psychology, 1982; 116(2):199–204.
10. Perry R, Lindell M. Predicting long term adjustment to volcano hazard. International Journal of Mass Emergencies and Disasters, 1990; 8(2):117–136.
11. Showalter P. Prognostication of doom: An earthquake prediction's effect on four small communities. International Journal of Mass Emergencies and Disasters, 1993; 11:292–297.
12. Peacock W, Brody S, Highfield W. Hurricane risk perceptions among Florida's single family homeowners. Landscape and Urban Planning, 2005; 73(2–3):120–135.
13. Baker E. Hurricane evacuation behavior. International Journal of Mass Emergencies and Disasters, 1991; 9(2):287–310.
14. Dash N, Gladwin H. Evacuation decision making and behavioral responses: Individual and household, 2005.
15. Gladwin C, Gladwin H, Peacock W. Modeling hurricane evacuation decisions with ethnographic methods. International Journal of Mass Emergencies and Disasters, 2001; 19(2):117–143.
16. Gladwin H, Peacock W. Warning and evacuation: A night for hard houses. P. 52 in Peacock W, Morrow B, Gladwin H (eds). Hurricane Andrew: Ethnicity, Gender, and the Sociology of Disasters. London: Routledge, 1997.
17. Norris F, Smith T, Kaniasty K. Revisiting the experience-behavior hypothesis: The effects of Hurricane Hugo on hazard preparedness and other self-protective acts. Basic and Applied Social Psychology, 1999;21:27–47.
18. Peacock W. Hurricane mitigation status and factors influencing mitigation status among Florida's single family homeowners. Natural Hazards Review, 2003; 4(3):149–158.
19. Lindell M, Perry R. Household adjustment to earthquake hazard. A review of research. Environment and Behavior, 2000; 32(4):461–501.
20. Cross J. Longitudinal changes in hurricane hazard perception. International Journal of Mass Emergencies and Disasters, 1990; 8(1):31–47.
21. Shaw W, Baker J. Models of location choice and willingness to pay to avoid hurricane risks for Hurricane Katrina evacuees. International Journal of Mass Emergencies and Disasters, 2010; 28(1):87–114.
22. Baker J, Shaw WD, Riddel M, Woodward RT. Changes in subjective risks of hurricanes as time passes: Analysis of a sample of Katrina evacuees. Journal of Risk Research, 2009; 12(1):59–74.
23. Weinstein N. The effects of personal experience on self-protective behavior. Psychological Bulletin, 1989; 105:324–333.
24. Burger J, Palmer M. Changes in and generalization of unrealistic optimism following experiences with stressful events: Reactions to the 1989 California earthquake. Personality and Social Psychological Bulletin, 1992; 18:39–43.
25. Helweg-Larsen M, Shepperd JA. Do moderators of the optimistic bias affect personal or target risk estimates? A review of the literature. Personality and Social Psychology Review, 2001; 5(1):74–95.
26. Shepperd JA, Helweg-Larsen M, Ortega L. Are comparative risk judgments consistent across time and events? Personality and Social Psychology Bulletin, 2003; 29(9):1169–1180.
27. Helweg-Larsen M. The lack of optimistic bias in response to the Northridge earthquake: The role of personal experience. Basic and Applied Social Psychology, 1999; 21:119–129.
28. Costa-Fontab J, Mossialosa E, Rudisill C. Optimism and the perceptions of new risks. Journal of Risk Research, 2009; 12(1):27–41.
29. Aucote HM, Gold RS. Changing perception of average person's risk does not suffice to change perception of comparative risk. Psychology, Health & Medicine, 2008; 13(4):461–470.
30. Avis NE, Smith KW, McKinlay JB. Accuracy of perceptions of heart attack risk: What influences perceptions and can they be changed? American Journal of Public Health, 1989; 79(12):1608–1612.
31. Dillard AJ, McCaul KD, Klein WMP. Unrealistic optimism in smokers: Implications for smoking myth endorsement and self-protective motivation. Journal of Health Communication, 2006; 11(Suppl 1):93–102.
32. Redmond EC, Griffith CJ. Consumer perceptions of food safety risk, control and responsibility. Appetite, 2004; 43(3):309–313.
33. Chapin J, Coleman G. Optimistic bias: What you think, what you know, or whom you know? North American Journal of Psychology, 2009; 11(1):121–132.
34. Andersson H. Perception of own death risk: An assessment of road-traffic mortality risk. Risk Analysis, 2011; 31(7):1069–1082.
35. Gardner M, Steinberg L. Peer influence on risk taking, risk preference, and risky decision making in adolescence and adulthood: An experimental study. Developmental Psychology, 2005; 41(4):625–635.
36. Flynn J, Slovic P, Mertz CK. Gender, race, and perception of environmental health risks. Risk Analysis, 1994; 14(6):1101–1108.
37. Clarke VA, Williams T, Arthey S. Skin type and optimistic bias in relation to the sun protection and sun tanning behaviors of young adults. Journal of Behavioral Medicine, 1997; 20(2):207–222.
38. DeJoy DM. An examination of gender differences in traffic accident risk perception. Accident Analysis and Prevention, 1992; 24(3):237–246.
39. Chock TM. The influence of body mass index, sex, and race on college students' optimistic bias for lifestyle healthfulness. Journal of Nutrition Education & Behavior, 2011; 43(5):331–338.
40. Walker EA, Mertz CK, Kalten MR, Flynn J. Risk perception for developing diabetes. Diabetes Care, 2003; 26(9):2543–2548.
41. Peterson LM, Helweg-Larsen M, Volpp KG, Kimmel SE. Heart attack risk perception biases among hypertension patients: The role of educational level and worry. Psychology & Health, 2012; 27(6):737–751.

42. Waters E, Klein W, Moser R, et al. Correlates of unrealistic risk beliefs in a nationally representative sample. Journal of Behavioral Medicine, 2011; 34(3):225–235.
43. Aalto A-M, Weinman J, French DP, Aro AR, Manderbacka K, Keskimski I. Sociodemographic differences in myocardial infarction risk perceptions among people with coronary heart disease. Journal of Health Psychology, 2007; 12(2):316–329.
44. Katapodi MC, Lee KA, Facione NC, Dodd MJ. Predictors of perceived breast cancer risk and the relation between perceived risk and breast cancer screening: A meta-analytic review. Preventive Medicine, 2004; 38(4):388.
45. Sargeant JM, Majowicz SE, Sheth U, Edge VL. Perceptions of risk and optimistic bias for acute gastrointestinal illness: A population survey. Zoonoses & Public Health, 2010; 57(7/8):e177–e183.
46. Weinstein ND. Unrealistic optimism about future life events. Journal of Personality and Social Psychology, 1980; 39(5):806–820.
47. Moen Br-E, Rundmo TR. Predictors of unrealistic optimism: A study of Norwegian risk takers. Journal of Risk Research, 2005; 8(5):363–382.
48. Campbell J, Greenauer N, Macaluso K, End C. Unrealistic optimism in internet events. Computers in Human Behavior, 2007; 23(3):1273–284.
49. Weinstein ND. Unrealistic optimism about susceptibility to health problems. Journal of Behavioral Medicine, 1982; 5(4):441–460.
50. Cho H, Lee J-S, Chung S. Optimistic bias about online privacy risks: Testing the moderating effects of perceived controllability and prior experience. Computers in Human Behavior, 2010; 26(5):987–995.
51. Parry SM, Miles S, Tridente A, Palmer SR. Differences in perception of risk between people who have and have not experienced salmonella food poisoning. Risk Analysis, 2004; 24(1):289–299.
52. McKenna FP, Albery IP. Does unrealistic optimism change following a negative experience? Journal of Applied Social Psychology, 2001; 31(6):1146–1157.
53. Halpern-Felsher B, Millstein S, Ellen J, Adler N, Tschann J, Biehl M. The role of behavioral experience in judging risks. Health Psychology; 2001; 20(2):120–126.
54. Lindell M, Perry R. Behavioral Foundations of Community Emergency Planning. Washington, DC: Hemisphere, 1992.
55. Sattler D. Repeated exposure to hurricanes and willingness to evacuate: Implications from the Hurricane Floyd experience. Pp. 69–76 in Maiolo J, Whitehead J, McGee M, King L, Johnson J (eds). In the Aftermath of Hurricane Floyd: Recovery in the Coastal Plain. Wilmington, NC: Coastal Carolina Press, 2001.
56. Sattler DN, Kaiser CF, Hittner JB. Disaster preparedness: Relationships among prior experience, personal characteristics, and distress. Journal of Applied Social Psychology, 2000; 30(7):1396–1420.
57. Kung Y, Chen S. Perception of earthquake risk in Taiwan: Effects of gender and past earthquake experience. Risk Analysis, 2012; 32(9):1535–1546.
58. Mishra S, Suar D. Do lessons people learn determine disaster cognition and preparedness? Psychology and Developing Societies, 2007; 19(2):143–159.
59. Whitmarsh L. Are flood victims more concerned about climate change than other people? The role of direct experience in risk perception and behavioural response. Journal of Risk Research, 2008; 11(3):351–374.
60. Agans RP, Shaffer LS. The hindsight bias: The role of the availability heuristic and perceived risk. Basic and Applied Social Psychology, 1994; 15(4):439–449.
61. Pachur T, Hertwig R, Steinmann F. How do people judge risks: Availability heuristic, affect heuristic, or both? Journal of Experimental Psychology: Applied, 2012; 18(3):314–330.
62. Tversky A, Kahneman D. Availability: A heuristic for judging frequency and probability. Cognitive Psychology, 1973; 5(2):207–232.
63. AAPOR. Standard Definitions: Final Dispositions of Case Codes and Outcome Rates for Surveys, 5th ed. Lenexa, KS: American Association for Public Opinion Research, 2008.
64. Cronbach L, Furby L. How we should measure "change": Or should we? Psychological Bulletin, 1970; 74(1):68–80.
65. Tisak J, Smith C. Defending and extending difference score methods. Journal of Management, 1994; 20(3):675–682.
66. Edwards J. Regression analysis as an alternative to difference scores. Journal of Management, 1994; 20(3):683–689.
67. Edwards J, Parry M. On the use of polynomial regression equations as an alternative to difference scores in organizational research. Academy of Management Journal, 1993; 36:1577–1613.
68. Liker J, Augustyniak S, Duncan G. Panel data and models of change: A comparison of first difference and two-wave models. Social Science Research, 1985; 14:80–101.
69. McArdle J, Hamagami F. Latent difference score structural models for linear dynamic analyses with incomplete longitudinal data. Pp. 139–175 in Collins L, Sayer A (eds). New Methods for the Analysis of Change. Washington, DC: American Psychological Association, 2001.
70. Cribbie RA, Jamieson J. Structural equation models and the regression bias for measuring correlates of change. Educational and Psychological Measurement, 2000; 60(6):893–907.
71. Edwards J. Ten difference score myths. Organizational Research Methods, 2001; 4(3):265–287.
72. Cohen J. Statistical Power Analysis for the Behavioral Sciences. New York: Academic Press, 1988.
73. Harris AJL, Hahn U. Unrealistic optimism about future life events: A cautionary note. Psychological Review, 2011; 118(1):135–154.
74. Shepperd JA, Klein WMP, Waters EA, Weinstein ND. Taking stock of unrealistic optimism. Perspectives on Psychological Science, 2013; 8(4):395–411.